HEAT STRESS IN IRRIGATED MAIZE

A Thesis

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by

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ABSTRACT

It is of critical importance to global food security and development that maize cropping systems maintain current levels of productivity under climate change, but our ability to develop targeted adaptation strategies is limited by uncertainty in predictions of crop response to high air temperatures. In this study, a statistical approach was used to identify crop responses to high temperature by controlling for management, location, soil moisture, and crop growth stage in nearly 2,000 yield values from the warmest region of the US Corn Belt. Results suggest that radiation, not temperature, is the most yield-limiting climate variable in irrigated maize production under optimal management. High temperatures during grain-fill impact yield gains from radiation, but yield response to high temperature during grain-fill is modified by prior temperature regime, suggesting mechanisms for thermo-acclimation in maize. Overall, climate explained only a small amount of yield variance relative to management, and slightly optimizing from within the range of current management practices was sufficient to offset any yield losses observed from high temperature. These results support the conclusions of Shaw *et al*. (2014) that multiple climate variables must be accounted for to accurately describe crop response to high temperatures. Limits to the applicability of econometric/statistical yield projections are discussed.

BIOGRAPHICAL SKETCH

Elizabeth Carter received her BS in Soil Science, *magna cum laude,* from the University of Massachusetts, Amherst, in 2009. While pursuing her undergraduate degree, she took a leave of absence to volunteer as a relief worker on the Gulf Coast after Hurricanes Katrina and Rita. She spent the final year of her undergraduate career at the University of Arizona in Tucson, studying biogeochemistry of desert soils and arid lands management. These two experiences taught her first-hand of the critical role that agricultural water use would play in sustainable development during the twenty-first century. After spending several years working in environmental and municipal consulting, she decided to pursue and MSc in Environmental Information Science to arm herself with the analytical skills needed to characterize water resources issues in a changing world.

For my daughters.

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LIST OF ABBREVIATIONS

ABBREVIATION	MEANING	PAGE DEFINED
AIC	Aikaike Information Criterion	33
APSIM	Agricultural Porduction Systems Simulator	11
Avg NT	Average high temperature (°C) between 7pm-7am	23
Avg Tmax	Average daily maximum temperature (°C)	23
AWDN	Automated Weater Data Network	19
BIC	Bayesian Information Criterion	36
EG	Early-Growth	29
G	Grain-fill	29
GCM	General Circulation Model	4
GDD	Growing Degree Day	20
HPRCC	High Plains Regional Climate Center	19
KDD	Cumulative degree-days with daily Tmax >29°C	23, 27
KDD 32	Cumulative degree-days with daily Tmax >32°C	23
KDD 34	Cumulative degree-days with daily Tmax >34°C	23
LMM	Linear Mixed Effects Model	31
lsmip	Least-square means interaction plot	47
ML	Maximum Likelihood	33
NASS	National Agricultural Statistics Service	3
NCGA	National Corn Growers Association	15
NT20	Cumulative degree-hours between 7pm-7am over 20°C	23, 28
NT22	Cumulative degree-hours between 7pm-7am over 22°C	23
NT24	Cumulative degree-hours between 7pm-7am over 24°C	23
PC1	Plane of highest correlation in PCA	41
PC2	Plane of second-highest correaltion in PCA, uncorrelated to PC1	41
PCA	Principal Component Analysis	41
RAD	Cumulative solar radiation (MJ/m2)	23
REML	Restricted Estimate Maximum Likelihood	32
S	Growing Season	29
Sen	Sensitive Period	29
Tc	Canopy Temperature	29
TT30	Cumulative degree-hours over 30°C	23, 27
TT32	Cumulative degree-hours over 32°C	23
TT34	Cumulative degree-hours over 34°C	23
TT36	Cumulative degree-hours over 36°C	23
VIF	Variance Inflation Factor	35
vpd	Vapor pressure deficit	10, 20
VPD	Averaged daily maximum vapor pressure deficit (kPa)	23

1 INTRODUCTION

1.1 PREDICTING MAIZE YIELDS UNDER CLIMATE CHANGE

Maize production plays a large and expanding role in modern development and global food security. More maize is produced on a weight basis than any other cereal crop (FAO, 2010). The ascendance of maize as a global staple is the result of its versatility, both in terms of productivity in a wide range of agro-ecological climates and in terms of its diverse agronomic and industrial uses. Well over half of the global maize crop goes to providing feed for animals (FAO, 2010), and in the United States—the largest maize-producing country—45% of the 2013 national maize crop was grown for biofuel production, up from 0.5% in 1980 (AEO, 2014).

In the coming century, the human population is expected to reach nine billion (UN, 2009). Diets are projected to continue to become more affluent, and the need for maize as animal feed is expected to increase as more of the population becomes able to afford eggs, milk, and meat (Msangi and Rosegrant, 2011). Biofuel production (such as corn-based ethanol) is expected to increase at a rate of 2.7% per year globally through 2040 (AEO, 2014). Between now and 2050 the need for maize in the developing world is expected to increase by 50% (Rosegrant *et al.*, 2009).

Closing the "yield gap" (the difference between observed and optimal yields) in developing regions has the potential to increase global maize production by 45% (Gustafson *et al.*, 2014). Recent research suggests that access to agricultural technology represents a significantly larger pool of crop yield variability than potential impacts of climate change (Gustafson *et al*., 2014; Mendelsohn and Dinar, 1999). Analysis of global maize yield potential under climate change, after compensating for this large potential for yield increase from closing the yield gap, requires evaluating the climate impacts on yields when maize is grown under optimal conditions. Accurate estimates of maize yield response to limiting climate conditions, as well as quantitative predictions of genetic, regional, and farm-level adaptation potential to these climate pressures, are essential information in planning for the sustained development of the human population.

Any predictions of the future are impeded by uncertainty, and when predicting yield response to climate change, there are multiple sources of uncertainty. Climate change models generate data that are different from current conditions, posing unique problems for model validation. The implicit lack of validation data sets in future climate change modeling leads to an unknown amount of inherent uncertainty in climate projections (Refsgaard *et al.,* 2014), which is compounded by uncertainty in future CO_2 emission and mitigation scenarios, as well as uncertainty generated from regional variability in weather patterns. Uncertainty in climate models becomes particularly problematic when predicting weather patterns at a local scale (Hawkins and Sutten, 2009). One change that can be predicted with both high confidence and very high likelihood is that, on average, there will be more warm days and nights and fewer cool days and nights, globally, as a result of climate change (Seneviratne *et al*., 2012).

1.2 YIELD PROJECTIONS FROM ECONOMETRIC MODELS

As climate models appear to perform best when predicting air temperature at coarse spatial resolution, in the past decade there has been a trend towards using statistical models to describe broad-scale relationships between maize yields and air temperature. These air-temperature/yield relationships are then projected onto modified climate data sets in an attempt to capture the magnitude of potential yield response to climate change. Taken as a whole, these studies paint an ambiguous picture of the risk posed to maize cropping systems by climate change.

Several studies in particular have produced startling results. Lobell and Asner (2003), attempting to parse concurrent yield gains related to management (including increased CO_2) from negative yield response to climate, concluded that actual yield trends (using National Agricultural Statistics, or NASS data) were 20% lower than what had been observed as possible because of climate change. Projecting from this dampening of the yield trend, they concluded that a 1°C increase in average growing season temperature could be associated with a 17% decrease in both maize and soybean yields. They also concluded that yields of these two crops were not significantly related to precipitation or radiation. Schlenker and Roberts (2009), using NASS data to project future yields from an observed non-linear association between maize yields and high temperatures, reported that maize yields could decrease by between 30-82% in the coming century as a result of increasing air temperatures under a mild and extreme climate change scenario, respectively.

Lobell *et al* (2011) identified an associative 1% and 1.7% decline for each day spent above 30°C in optimal rain-fed and in drought conditions, respectively, in African maize yield-trial data. They projected that 65% of the continent could face yield losses from a 1°C warming under optimal rain-fed conditions, and that 100% of the continent would face yield losses from a 1°C warming scenario under drought conditions. Though the use of irrigation modified the projected magnitude of the yield loss, the authors found air temperature to be a robust predictor of maize yields, even if the mechanisms for this yield response could not be discerned. Schlenker and Lobell (2010) projected a 22% decrease in maize yields by 2050 in Sub-Saharan Africa from an observed relationship between air temperatures and yields, and suggested that: "well-fertilized modern seed varieties are more susceptible to heat related losses."

Urban *et al*. (2012) predicted an 18% decline in rainfed maize yields by 2030, and also predicted that the coefficient of yield variability would increase by 47% with increasing temperatures. This was based on an observed temperature-yield relationship in 50 years of county-level yield average (from NASS data) which had been projected onto temperature and precipitation outputs of 15 different general circulation models (GCM). They note that the relationship between yield and temperature used to make these projections explained only 5-11% of the total yield variance in their model, with most of the yield variance explained by an un-parameterized linear trend towards increasing yields since 1950. They also concluded that yield response to air temperature was not significantly modified by precipitation.

As maize is grown world-wide, in regions with different temperature regimes, the definition of high temperatures varies considerably over space. This suggests that locally variable factors affecting maize cropping systems, ranging from genetics to soils to management to complex climate interactions, can modify crop yield response to high temperature. Li *et al.* (2011), using an econometric model that looked at maize yield response (from USDA Economic Research Service and the 2008 China Statistics Yearbook) to climate while accounting for economic and farm-technology based variables, showed that yield response to climate change (indicated by metrics of temperature and precipitation) was not entirely positive or negative, but varied significantly from region to region. According to Butler and Huybers (2013), by adjusting for spatial adaptation to heat stress, modeled net losses to yields due to air temperatures were averted under climate change scenarios. Lobell and Asner (2003) also observed that yield response to temperature varied spatially, with some regions in the US Corn Belt showing positive yield response to hot, dry years, and some regions showing positive yield response to cool, moist years.

1.3 VARIABILITY IN PROJECTED MAIZE YIELDS

As a whole, statistical/econometric yield projections based primarily on temperature show quite a wide range of results (Challinor *et al,* 2014). There is considerable variability in both the sign and magnitude of coefficients of yield response to increasing temperature, with yield projections over the next century ranging from dire (up to 82% yield decline under an extreme warming scenario in Schlenker and Roberts, 2009) to neutral (Butler and Huybers, 2013; Moore and Lobell, 2014), to positive (with up to 45% yield increases under climate change with improved cultivars in Tao and Zhang, 2010). Differences in magnitude of modeled relationships between maize yields and high temperatures seem to be rooted in model parameterization, control for management (especially irrigation), model spatial structures, model temporal structures (especially differing quantifications of yield trends), selection of climate variables, adjustments for increasing CO_2 concentrations, region of yield data used for model fitting, and quality of yield and climate data used for model fitting.

Still, the prevalence of this methodological approach appears to be associated with a growing consensus that temperature will be the climate variable that will be exerting the strongest control over maize yields in the coming century in statistical/econometric yield projections (Ortiz-Bobea, 2015). According to Roberts *et al*. (2013), "the harmful temperature effect above the optimum [is] the single most powerful predictor of yield, and extremely robust across many different lines of statistical identification." However, this statistical/econometric approach to characterizing crop response to climate change is especially problematic when mechanisms for this heat stress response are poorly defined. An understanding of crop responses to heat stress is essential for interpreting results of statistical yield models. Understanding the magnitude of heat stress response, especially in relation to other sources of yield variability such as we see from management, is needed to identify and evaluate the potential of targeted adaptation strategies.

1.4 MANAMGEMENT AND ADAPTATION

There are numerous studies presenting evidence that crop management can significantly interact with crop response to climate. Winstanley and Changnon (1999) showed that cultural shifts related to genetics and agricultural technology in the 20th century modified yield response to multi-dimensional "seasonal climate conditions," suggesting that maize cropping systems have already demonstrated adaptation to climate. Many studies have shown that altering cultural practices, such as planting rate (Tokatlidis and Koutroubas, 2003; Finger *et al*., 2010), planting date (Tao and Zhang, 2010; Finger *et al*., 2010; Liu *et al.,* 2013; Challinor *et al.,* 2014), cultivar maturity class (Tao and Zhang, 2010; Liu *et al.* 2013;), irrigation (Finger *et al,* 2010; Challinor *et al,* 2014), and soil management (Aguilera *et al*., 2013), can positively or negatively modify maize yield response to climate. While these studies reach quantitatively variable conclusions about the potential for maize cropping systems to adapt climate change through modified management, all agree that mechanisms for adaptation exist.

Among the most common adaptation strategies considered is use of improved genetics (Challinor *et al,* 2014). Yield response to temperature appears to be mediated by cultivar-specific response to high temperatures. Maize is locally adapted to a very wide range of climates, and variable responses to heat stress have been observed between cultivars from regions with different temperature regimes (Duncan and Hesketh, 1968). In addition to spatial variability in genetic heat-stress response of maize cultivars, tolerance of climate stress has been increasing in maize cultivars over time. Several studies link increased yield potential of cultivars during the 20th century to genetic selection for increased stress tolerance (Russell, 1999; Tollenar and Lee, 2009; Duvick, 2005), including drought tolerance (Gholipoor *et al*., 2013). Tao and Zhang (2010) showed that selecting heat-tolerant varieties and locally optimizing cultivar maturity class could more than offset climate-change heat-induced yield declines, projecting significant yield gains by 2050 in these genetically adapted systems. A recent study by Smith *et al.* (2014) concluded that "more effective use of genetic diversity and crop management will allow U.S. maize breeders and farmers to accommodate climate change for the foreseeable future."

1.5 MOISTURE STRESS

High temperature and low moisture are correlated in many climate systems, making it difficult to determine if high temperatures have an impact on maize yields independent of moisture stress. A number of statistical and econometric analyses have looked at yield response to high temperature after accounting for moisture through precipitation, or vpd. Hawkins *et al*. (2013) showed that French maize yield response to precipitation was of greater magnitude than yield response to temperature until 2000, after which the decreasing role of precipitation was attributed to increasing rates of irrigation in French maize production. They also note that, even with increasing incidence of irrigation, increased precipitation significantly and positively modified yield response to temperature. Ortiz-Bobea, 2012) noted, in agreement with physiological literature, that yields were highly sensitive to soil moisture around silking, and that accounting for soil moisture reduced projected yield losses under a moderate climate change scenario by 100%. Urban *et al.* (2015) showed that precipitation positively modified negative yield impacts from increasing vpd, but not completely. These results indicated that there may still be unexplained temperature impacts on maize yields that are independent of soil moisture stress. In contrast, in a study looking at NASS yield data mainly in irrigated counties, Shaw *et al*. (2014) reported that irrigated yields only had a very weak response to increasing temperature, and showed that years with high moisture stress were highly leveraging identified trends between temperature and non-irrigated yields. When these years of extreme moisture anomaly were excluded from the data set, previously established relationships between maize yields and temperature extremes in rainfed counties nearly disappeared.

1.6 YIELD PROJECTIONS FROM PROCESS-BASED CROP MODELS

In many recent statistical/econometric models, heat stress is defined as accumulation of thermal time above a given threshold (generally 29°C) over the entire growing season, or during a set interval around silking, when physiological processes directly related to yield formation occur and where stress, including heat stress, can potentially reduce yield (Cicchino et al., 2010; Roberts *et al*., 2013). One inherent limitation of this approach is that it does not identify possible mechanisms of heat stress. Many statistical models, therefore, have limited usefulness when it comes to identifying targeted adaptation strategies. To compensate for this, another popular approach to climate-adjusted yield projections involves the use of process-based crop models.

Process-based crop dynamic simulation models generate yield projections by simultaneously modeling basic soil/crop/atmosphere processes combined with empirically derived relationships between soils, genetics, management, and climate, dynamically over time. Crop process models often contain parameters for yield response to climate, which have been derived from experimental observations of climate-crop interactions. These parameters for crop response to climate in process-based models can be used to make predictions of yield response under climate projections.

In many of the most commonly used crop process models, parameterized heat stress mechanisms include associations with soil moisture stress, accelerated rates of phenologic development (though this is not generally modified by temperatures above a pre-defined upper temperature limit), or increased respiration rates. Based on how temperature impacts are defined, different crop process models can generate variable yield projections when applied to climate change scenario datasets (Asseng, 2013). Using the crop model APSIM (Agricultural Production Systems Simulator), Lobell *et al*. (2011) compared maize yields modeled with trended and de-trended climate data to conclude that global maize yields had declined by 3.8% between 1980 and 2008, but the observed yield decline did not result in net yield losses. Instead, they concluded that climate losses were nearly sufficient to offset gains from CO_2 enrichment or technology trends. Lobell *et al*. (2013) use APSIM again to identify the mechanism of heat-induced yield decline. They conclude that US maize yields can be expected to decline by 13% due to increased vapor pressure deficit (vpd). Because vpd is an indicator of atmospheric moisture "demand," it has been considered a proxy for plant water availability (Roberts *et al*., 2013). Lobell *et al*. (2013) found agreement between the APSIM simulation and a statistical model predicting yields based on temperature, and concluded that, based on the APSIM simulation, heat stress was related to yield decline due to the association between high temperatures and high vpd's. The way that APSIM is parameterized, high vpd is related to more rapid onset of soil moisture stress, which reduces yields. They conclude that temperature is still the key driver for observed yield declines, but that the mechanism is indirect—operating through vpd and associated with moisture stress.

As a whole, process-model based yield projections predict modest maize yield losses to yield gains under climate change scenarios (Roberts *et al*., 2013). The lack of agreement between maize yield projections under future climate scenarios made by crop process-models and statistical/econometric models is the source of some debate. For example, there are questions of whether statistical models are structurally capable of parsing complex interactions that impact yield formation in a given environment, particularly crop response to variable precipitation and soil moisture stress. Alternatively, there are questions about whether crop process models have adequately parameterized crop responses to high temperature (Roberts *et al*., 2013; Rivington and Koo, 2010). As stated by Roberts *et al*. (2013), large discrepancies between yield projections from crop process-based models and yield projections from statistical models mean that "either statistical models lack critical features of crop science or crop science lacks critical temperature effects, or more likely, each approach lacks some feature of the other."

Though air temperature is predicted with the most certainty in GCM's, the magnitude of crop yield response to high temperature is still not well established in econometric and process-based crop models. Lobell *et al*. (2013) found that statistical models based on precipitation were better able to match predictions from crop-process models, but that the statistical model was less accurate when predicting from observed temperature trends. Similarly, Watson *et al*. (2014) determined that errors in crop yield projections based on temperature data alone had a much stronger influence on yield projections, in both process-based and econometric yield projection models, than errors in crop yield projections based on other climate variables, such as precipitation. Asseng *et al*., 2013 concluded that uncertainty in crop model projection increases with increasing temperature, and that "a greater proportion of the uncertainty in climate change impact projections was due to variations among crop models than to variations among downscaled general circulation models." Though temperature is the climate variable currently predicted with the most certainty in general circulation models, maize yield response to current and future high temperature events is still not well-established, in part because the physiological mechanisms for temperature-related yield decline are unclear.

Current projections from crop process-based models seem to implicate soil moisture stress as the main biophysical driver of reduced maize yields that are associated with increasing temperature, but some the magnitude of projected yield loss with econometric models suggests that heat stress impacts on maize yields, independent of moisture stress, may exist. If high air temperatures have significant impacts on yields, independent of soil moisture stress, identifying the mechanisms and magnitudes of explicit temperature stress impacts are essential for adequately parameterizing crop models for above-optimum temperature effects, validating statistical models, and selecting and quantifying the mitigation potential of targeted adaptation strategies.

The objectives of this study were three-fold. First, we wanted to quantify yield impacts of heat stress in maize, if any, in the absence of soil moisture stress and after adjusting for accelerated rates of phenologic development. Second, we wanted to determine if a statistical approach could be used to identify possible mechanisms for heat stress in maize, by accounting for the timing of the heat stress relative to crop development, and by considering multiple climate variables. Third, we wanted to quantify the relative impacts of management and climate on yield to evaluate the adaptation potential of maize production systems under optimal management.

2 METHODS AND MATERIALS

2.1 STUDY AREA

The United States Corn Belt, which includes the Midwestern and North Cental states of North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa, Missouri, Wisconsin, Illinois, Ohio, Michigan, and Indiana, is responsible for the majority of maize production in the United States, which in turn produces 32% of the world's maize crop (USDA NASS, 2010). This study uses irrigated maize yields and climate data from the states of Kansas, Nebraska, and Missouri. These three states were selected primarily because of extensive irrigated maize production and, consequently, large numbers of irrigated contest entries (see "Yield Data") throughout the study period (2005-2012). The climate experienced in these three states is representative of a wide range of the climate variability experienced in the United States Corn Belt; including the portions of the Corn Belt with the highest mean growing season temperatures (southwestern Kansas and southern Missouri). Figure 2.1 shows the distribution of precipitation (left) and average air temperature (right) during the month of July across the region (U2U Decision Support Tools Climate Patterns Viewer, https://mygeohub.org/groups/u2u/cpv).

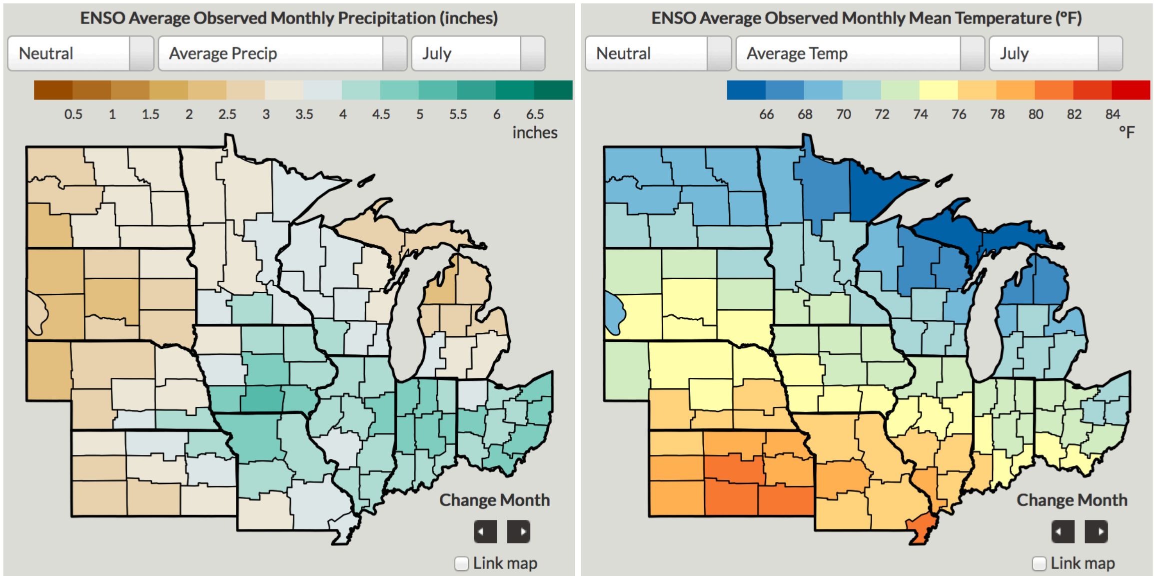

Figure 2.1: Distribution of July precipitation and July average temperature across the US Corn Belt.

Precipitation decreases gradually on a south-east to north-west gradient across the region, with mean annual precipitation reaching up to 50” in southeastern Missouri and as low as 5” in northwestern Nebraska. Temperatures follow a north-south gradient, with attenuation in the east, with the hottest temperatures seen in southern Kansas and southeastern Missouri. The average growing season temperatures during the study period ranged from 16°C to 26°C, with maximum observed growing season temperatures ranging from 33.5°C to 43.9°C.

2.2 YIELD DATA

The National Corn Grower’s Association (NCGA) National Yield Contest, initiated in 1964, challenges U.S. corn growers to reach the highest yield potential of modern cultivars. The NCGA is one of the primary maize commodity and advocacy organizations in the United States, with 42,000 farmer-members in the 2014 organizational report. In the most recent growing season, 8,129 contest entries were received, and contest winners continued a long-standing tradition of setting world record-breaking yields. This maize yield data set is unique in that it represents a body of growers who aim to approach or achieve the theoretical yield potential of modern cultivars, thereby giving unique access to climate-induced yield variability. In addition, yield contest data includes county of entry, farm ID, planting date, planting rate, previous crop, tillage treatment, and cultivar name for each yield record. Access to management information allows us to examine the magnitude of yield response to climate relative to the yield response to a range of high-performing management practices in the U.S. Corn Belt. Access to planting date and cultivar allows us to determine the timing of the heat stress in crop development. Location of the yield contest entry allows us to examine unexplained spatial structure in the yields, although the spatial resolution is limited since the data are reported by county.

Since yield contest competitors must pay to enter, we assume that yields are from plots at or near optimal management, above and beyond even what is economically optimal. By looking at yield values under optimal management—where we assume that soil moisture, fertility, and pest control are not limiting—we are essentially examining yield variability in a population of yield values that are at or near the theoretical yield potential, or point where yields are limited only by genetics and climate.

For this analysis, we used all contest entries from irrigated classes in the study area between the years of 2005-2012 totalling nearly 2,000 yield records. Figure 2.2 gives an overview of management parameters employed in the production of irrigated entries.

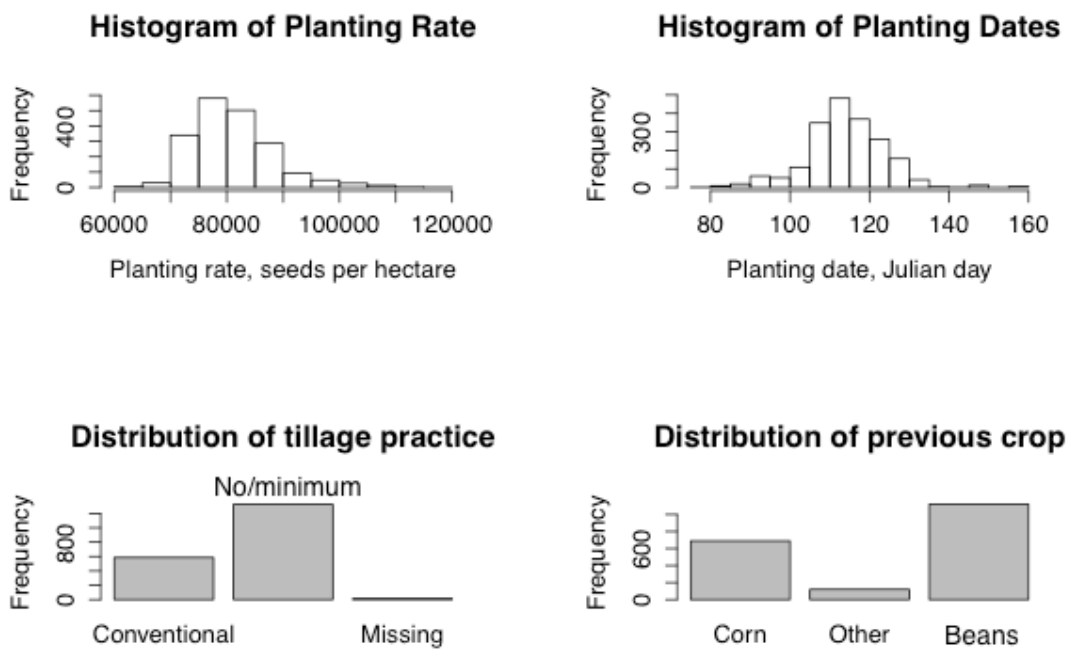

Figure 2.2: Management parameters in irrigated yield contest entries.

Many regression analyses that examine yield response to climate variables look specifically at the fluctuations in mean yield among years (yield anomaly), often after adjusting for a linear trend of increasing yields over time. In order to investigate relationship between climate and inter-annual yield anomaly, a study period must include significant difference in mean yields between years. The mean yield of irrigated yield contest entries was 16.72 MT/ha (with a standard deviation of 1.76 MT/ha). Using a Tukey's Honestly Significant Differences Test with a 95% confidence interval, we see that significant inter-annual differences among irrigated yield-year pairs were identified, with 2009 and 2012 producing yields that are significantly higher than other years (Figure 2.3).

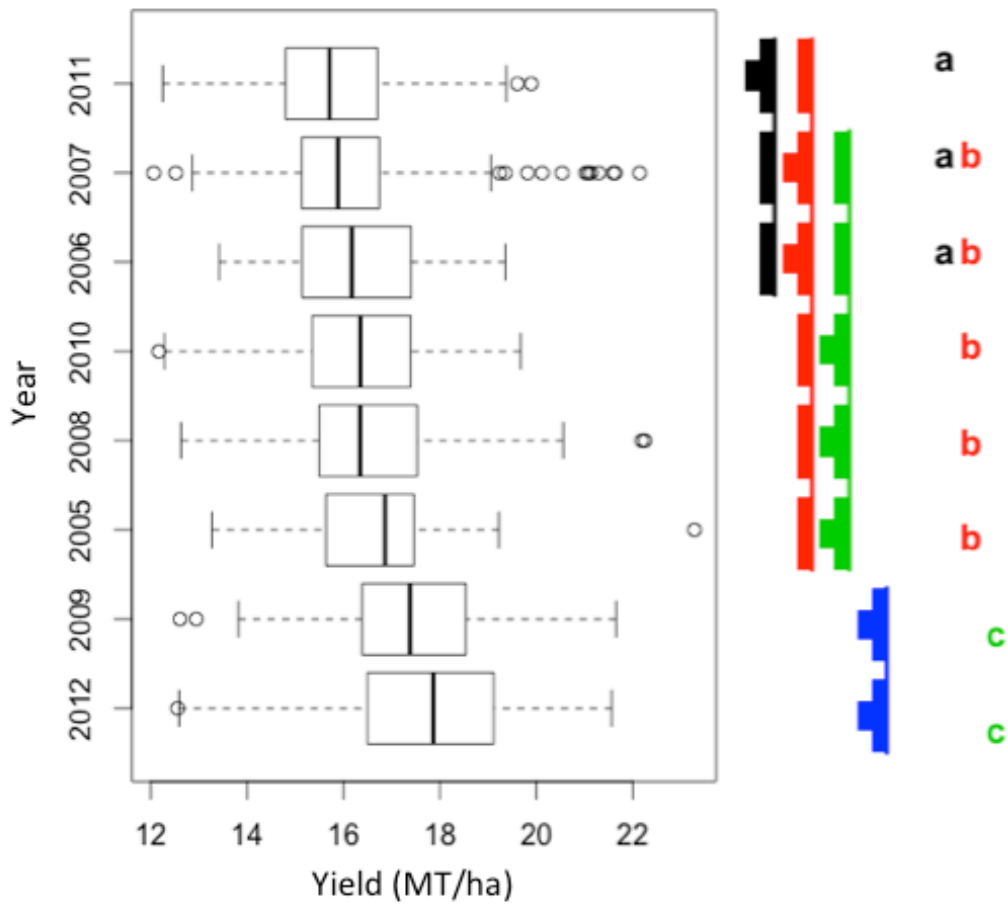

Figure 2.3: Boxplot of irrigated yields by year. Letters indicate yield-year pairs that are not significantly different at a 95% confidence interval, as determined by a Tukey's Honestly Significant Differece (HSD) test performed on yield by year combinations. The colored, horizontal "Ts" of the graph indicate which year pairs have the same pattern of "significant" or "insignificant" differences; similar year pairs are represented by a "T's" which come nearest to touching (image generated using multcompView package in R).

2.3 CLIMATE DATA:

Historic hourly climate data from 66 weather stations in Nebraska, Kansas, Colorado, and Missouri were used to calculate a number of climate variables (Table 2.1). Weathers stations in Kansas, Colorado, and Nebraska are all managed by the High Plains Regional Climate Center (HPRCC) Automated Weather Data Network (AWDN). Historical climate data for Missouri yield contest entries was provided by the Missouri Mesonet, which was established by the Commercial Agriculture Program of the University of Missouri Extension.

Hourly climate data was processed for errors using the flagging systems implemented by the HPRCC and Missouri Mesonet, as well as through visual analysis and maximum/minimum plotting. The data was determined to be of relatively high-quality. As hourly radiation data was not available from Kansas weathers stations using online data services at the HRPCC, hourly solar radiation was extrapolated from daily cumulative solar radiation using a sinusoidal curve.

Hourly vapor pressure deficit, or difference between current air moisture and the amount of water the air can hold at saturation, was calculated using measured incident solar radiation, air temperature, and relative humidity based on the method outlined by Snyder and Pruit (1985) (Equations 2.1-2.3).

To obtain saturation vapor pressure (es, kPa), where Ta (°C) is an hourly temperature measurement:

$$es = 0.618 * \frac{exp^{17.27*Ta}}{Ta+237.3} \qquad (2.1)$$

To obtain hourly vapor pressure (ea, in kPa) from saturation vapor pressure (es, kPa) and percent relative humidity (RH):

$$ea = es \times \frac{RH}{100} \qquad (2.2)$$

To obtain hourly vapor pressure deficit (vpd, in kPa)

$$vpd = es - ea \qquad (2.3)$$

Daily maximum and minimum air temperatures were used in two Growing Degree Day (GDD) calculations. We calculated GDD 30°C/10°C (hereafter referred to as GDD 86°F/50°F), as it is the industry standard for US seed companies reporting thermal time for silking and maturity. We also calculated GDD 34°C/8°C as per the method outlined in Otegui and Bonhomme (1998) for using thermal time to model the duration of growth development phases which are critical to yield formation.

Hourly climate data were matched to yield records based on two spatial criteria. For each year in the study period, the growing degree day (GDD 86°F/50°F) for the region was calculated as a raster format map using the U.S. degree-day mapping calculator, 4.0 (Coop, 2010). These maps were used to calculate the average growing season GDD 86°F/50°F for every county containing a yield contest entry in that year, and were also used to determine the growing season 86°F/50°F at the location of all weather stations. For each yield contest entry, all weather stations within a range of +/- 200 growing degree days (GDD 86°F/50°F) were listed. From these weather stations with a range of +/- 200 GDD 86°F/50°F, the nearest was selected. Un-interpolated weather data from this nearest station was taken as the best approximation of weather conditions experienced by the crop, and data from this station was used to calculated climate variables associated with the yield value.

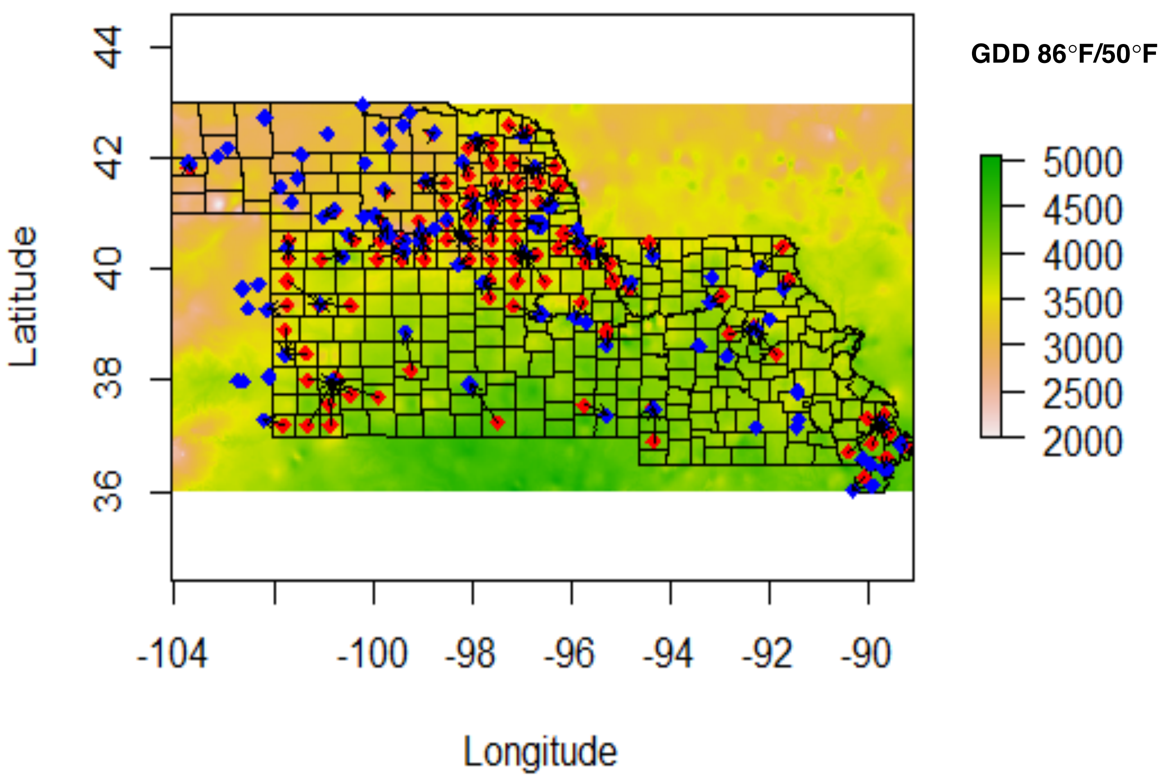

Figure 2.4: Map of weather station associated with yield values (2012). County centers associated with irrigated yield contest entries are indicated with red dots and weather station locations are shown in blue. Arrows indicate which water stations' data was used to calculate climate and heat stress indices for a given yield contest entry in a give year. Color scale indicates the GDD 86°F/50° accumulated over the 2012 growing season at a given location.

2.4 MECHANISMS OF HEAT STRESS: STATISTIAL APPROACH

2.4.1 Overview

The most commonly parameterized impacts of high temperature in crop process-based models are increased rate of phenologic development, and high temperature associated moisture stress (Section 1.5), yet recent statistical/econometric analysis of temperature impacts on yields indicate the potential of additional un-parameterized heat-stress mechanisms that may limit future productivity of maize cropping systems (Section 1.6). The first objective of this study was to identify potential heat stress mechanisms in maize cropping systems after soil moisture stress and increased rates of phenologic development had been accounted for. To control for soil moisture, we only examined irrigated yields under optimal management. To control for accelerated development rates, we modeled the duration of maize growth and development using thermal time. We were able to do this because we knew the specific cultivar that was planted, and therefore the GDD to silking and maturity for that cultivar (Section 2.4.2).

To determine temperature stress impacts independent of increased development rates, we looked at accumulation of degree-hours over 34°C. Temperatures above 34°C did not have any impact on modeled phenologic development, as we used GDD 34°C/8°C to determine the duration of crop growth and development (Section 2.4.2). Finally, to get at specific temperature stress mechanisms, we calculated accumulation of heat stress, as well as other climate variables (Table 2.1) during three thermal-time defined growth development phases, yield-associated planting dates, and cultivar-specific GDD to silking and maturity.

Table 2.1: Climate variables, including temperature stress indices, and abbreviations.

Abbreviation	Climate Variable
Avg Tmax	Average daily maximum temperature
TT30	Cumulative degree-hours over 30^{o}C
TT32	Cumulative degree-hours over 32^{o}C
TT34	Cumulative degree-hours over 34^{o}C
TT36	Cumulative degree-hours over 36^{o}C
KDD	Cumulative degree-days with daily Tmax >29^{o}C
KDD 32	Cumulative degree-days with daily Tmax >32^{o}C
KDD 34	Cumulative degree-days with daily Tmax >34^{o}C
Avg NT	Average high temperature (^{o}C) between 7pm-7am
NT20	Cumulative degree-hours between 7pm-7am over 20^{o}C
NT22	Cumulative degree-hours between 7pm-7am over 22^{o}C
NT24	Cumulative degree-hours between 7pm-7am over 24^{o}C
RAD	Cumulative solar radiation (MJ/m2)
VPD	Averaged daily maximum vapor pressure deficit (kPa)

By examining yield impacts of temperature at specific phases in crop development, and by looking at specific combinations of climate indices along with temperature, we hoped to identify specific mechanisms for heat stress that could be then linked to specific adaptation mechanisms. Table 2.2 demonstrates the concept behind using timing (growth development phase, see Figure 2.5) and climate variables (Table 2.1) to determine if there is evidence for temperature-associated yield decline and to indicate possible mechanism(s) of action. Specific adaptation mechanisms which could be explored in the event of an observed heat stress mechanism are also included.

Table 2.2: Heat stress mechanism by crop growth stage and climate variable for irrigated maize. TT is degree-hours over a given temperature threshold, RAD is cumulative incident solar radiation, AvgNT is average temperature between 7pm-7am, and VPD is average daily maximum vapor pressure deficit.. Under "Indicator variable" a '+' between two variables means that both would be significant predictor variables, a ':' between two variables means that both variables would be significant with an interaction term, and an ',' means that either climate variable could indicate the stress mechanism (but only one variable would be needed). Colors indicate growth development stage associated with heat stress mechanism, and correspond with the colors used in Figure 2.5.

Stress Mechanism	**Growth Development Period:**				**Indicator Variable:**	**Adaptation Mechanism:**
	Early Growth	Sensitive	Grain-fill	Whole season		
Systemic weakness: cellular damage					TT	improved genetics
Systemic weakness: structural photosynthate lost to respiration					TT + RAD	> maturity class, improved genetics
Systemic weakness: accelerated phenologic development					AvgNT, RAD	> maturity classs, earlier planting
Reduced kernal number: pollen desication					VPD	improved genetics (descrease ASI), earlier planting
Reduced kernal number: kernel abortion					TT + RAD	improved genetics
Reduced kernal weight: starch-building photosynthate lost to respiration					TT+RAD	> maturity class, improved genetics, earlier planting
Reduced kernel weight: radiation use efficiency					TT : RAD	> maturity class, improved genetics
Reduced kernel weight: accelerated phenologic development					Avg NT, RAD	> maturity class, earlier planting

2.4.2 Growth development phases by thermal time

After observing that there was a lack of consistency in the literature in defining length of growth development phases between variable agro-ecological zones and climate-years, Otegui and Bonhomme (1998) developed a system for determined the duration of climate-sensitive physiological processes using thermal time (mainly based on addressing ear elongation). Based on their system, we separated the growing season into three distinct phases; “early growth,” “sensitive period,” and “grain-fill” (Figure 2.5).

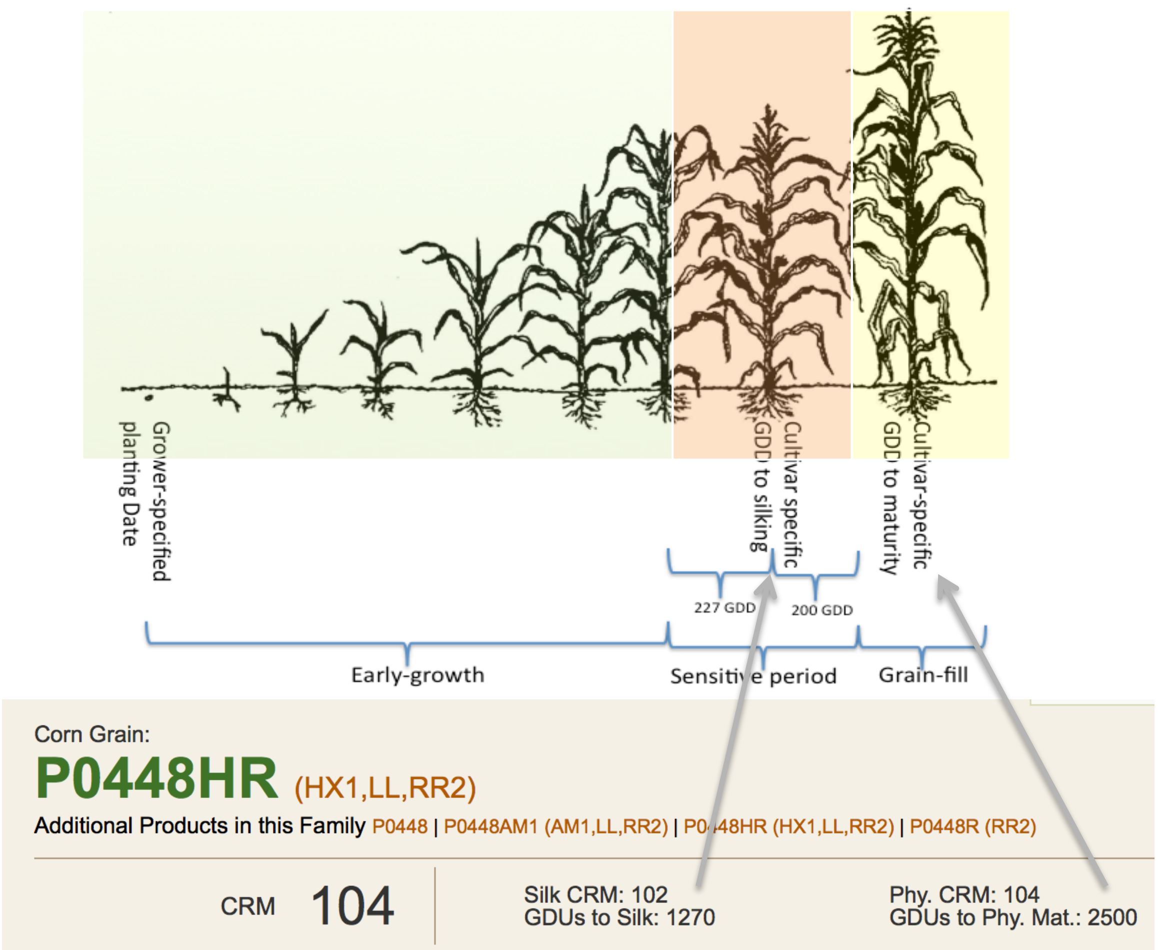

Figure 2.5: Schematic showing how the three growth-development phases were calculated using thermal time. Detail at bottom is from a product description of a maize cultivar (P0448HR) from the Pioneer® Website (www.pioneer.com) showing GDD to silking and to maturity.

Using the grower provided planting date, company provided cultivar-specific GDD 86°/50°F to silking and maturity, and GDD 86°/50°F modeled using daily maximum and minimum temperatures from the weather station nearest to the yield record (within a range of +/- 200 GDD to county of yield record), the approximate silking date and maturity date for every yield record were determined. Climate and temperature stress indices were calculated for the entire "growing season," defined from the planting date until the date when cumulative GDD reached the company-specified cultivar GDD to maturity and for the three growth phases described below.

The first growth development stage, "early growth," is defined as the period from the record-specified planting date to the onset of kernel number (KN) development (silking date – 227 GDD 34°C/8°C). 'Sensitive' is the period from the onset of KN development to the beginning of the linear grain-fill period (silking date+ 200 GDD 34°C/8°C) (Otegui and Bonhomme, 1998). Grain-fill is the period from the onset of linear grain-fill (silking date + 200 GDD 34°C/8°C) to physiological maturity.

As cumulative incident solar radiation was calculated by thermal-time defined intervals, yield impacts from increased rates of phenologic development would be captured through yield gains from radiation (see Table 2.2). Like many of the climate variable combinations analyzed, using cumulative incident solar radiation as a proxy variable for increased phonologic development is complicated by multiple overlapping mechanisms of potential yield response to a climate variable. Yield response to increased radiation in irrigated systems under optimal management would be expected to be significant even if the duration of the growing season (the period over which incident radiation was summed) was not controlled for using thermal time. We did not standardize years with increased radiation from decreased cloud cover from years which would have indicated increased radiation from low growing season temperatures, and therefore low accumulations of GDD's over the growing season.

2.4.3 Description of climate indices

Climate indices (thermal stress indices identified from the literature, cumulative incident solar radiation, vapor pressure deficit, and night-time temperature indices) were calculated for each of the three growth development phases, as well as for the entire growing season,. Table 2.1 defines the climate variables used and their acronyms. Cumulative solar radiation (RAD) was determined by summing the hourly averaged incident solar radiation (in W /m^2 hr) over the period of time being examined, and converting to MJ/m^2. Temperature threshold (TT) indices are cumulative degree-hours (°C hr), where an hourly measurement of air temperature (Tm) exceeds a given threshold (T_o) (Cicchino *et al.*, 2010), as in equation 2.7.

$$\mathrm{TT} = \sum_{i=1}^{n}(\mathrm{T}m_i i - \mathrm{To}) \text{ , for Tm } > \text{ To} \qquad (2.7)$$

Killing Degree Days (KDD), sometimes called extreme degree days (EDD) or extreme heat degree days (HDD), is a temperature stress index which has been used extensively in recent studies on heat stress in crop production as a means of quantifying crop exposure to above-optimum temperatures (Schlenker *et al.*, 2013; Butler and

Huybers, 2013; Shaw *et al.,* 2014; Lobell *et al.* 2011; Roberts *et al,* 2013; Lobell *et al.* 2013). KDD is similar to the TT indices, but represents degree-days (°C day) where daily maximum air temperature (Tdm) exceeded a given threshold temperature (Tdo) (Equation 2.8).

$$\text{KDD} = \sum_{i=1}^{n}(Tdm_i - Tdo\ ),\ \text{for Tdm} > \text{Tdo} \qquad (2.8)$$

For both the TT and KDD indices, we noted a wide range of variability in the literature on what constituted the threshold high temperature, and so we chose to examine multiple threshold temperatures (Tdo). While regression results from multiple thresholds are reported in results, the final model was constructed using TT34. TT34 was selected mainly because it only considers temperatures that are above the optimum temperature threshold for our growing degree day calculations (GDD 34°C/8°C), see section 2.4.2. Vapor pressure deficit (vpd) was calculated hourly for each climate file (Section 2.3). Maximum daily vpd was determined, and then the daily maximum vpd were averaged over the time period of interest to get at mean daily maximum vpd (VPD, in kPa).

Though high night temperatures are generally regarded as being detrimental for maize yields (Cantarero *et al.*, 1999; Chang, 1981), there is little consensus in the literature defining stressful night temperatures. We chose to look at average night temperature, averaging first the hourly air temperature between 7pm and 7am daily, then averaging the daily mean night temperature over the period of interest. We also examined a night temperature threshold (NT) index that operates similarly to the TT index described above, but only considering hourly temperatures occurring between 7pm and 7am daily, with T_o set at 20°C, 22°C, 24°C, and 26°C.

Each climate variable was calculated for the three growth development phases, as well as for the entire growing season. Variables representing entire growing season are prefixed with an “S”, variables representing early-growth are prefixed with an “EG”, variables representing “sensitive” period conditions are prefixed with a “Sen”, and variables representing grain-fill conditions are prefixed with a “G”

2.4.4 Modeled Canopy Temperature

Shaw and Riha (in preparation) used data from an eddy covariance tower located in an irrigated maize field in southeastern Nebraska to empirically derive a relationship between maximum irrigated canopy temperatures (T_c, in °C) and daily maximum air temperature (T_{max} in °C), daily maximum incident solar radiation (R_{max}, W/m^2), and daily maximum vapor pressure deficit (vpd_{max}, kPa). This relationship (Equation 2.9) was used to model maximum daily canopy temperature in irrigated maize yield contest entries for every day in each yield-specific growing season.

$$T_C = T_{max} + 0.233 - 1.11 \times vpd_{max} + 0.00202 \times R_{max} \qquad (2.9)$$

Daily maximum canopy temperature in excess of 29°C, 32°C, and 34°C were used to calculated canopy KDD stress indices for the irrigated maize yields (Equation 2.8).

In summary, the duration of the growing season and growth development phases was determined uniquely for each yield contest entry based on the relationship between the cultivar's maturity class and the accumulated thermal time at the entry's time since planting and location. These four time frames (entire growing season, early growth, sensitive period, and grain-fill) were used as the timespans in which to calculate four sets of the climate indices per yield entry. All temperature stress and climate indices by growth development period were returned to a data frame containing yield, farm identifier, county, weather station identifier, planting date, planting rate, previous crop, tillage, and cultivar. This data frame was used for statistical analysis.

2.5 LINEAR MIXED-EFFECTS MODELING

2.5.1 Factor selection and model construction

The structure of the yield contest data provided some interesting challenges for statistical modeling. Yields values come from farms. Some farms submit multiple contest entries in a year with different management parameters, and some farms submit entries for multiple years. Farms are imperfectly nested in counties, as some farms submit yield contest entries in more than one county.

Because we are also trying to determine whether there is spatial or temporal modification of climate induced yield response, determining whether climate variables are impacting inter-annual or spatial yield variability is important. Figure 2.6 shows a schematic of the structure of the yield data.

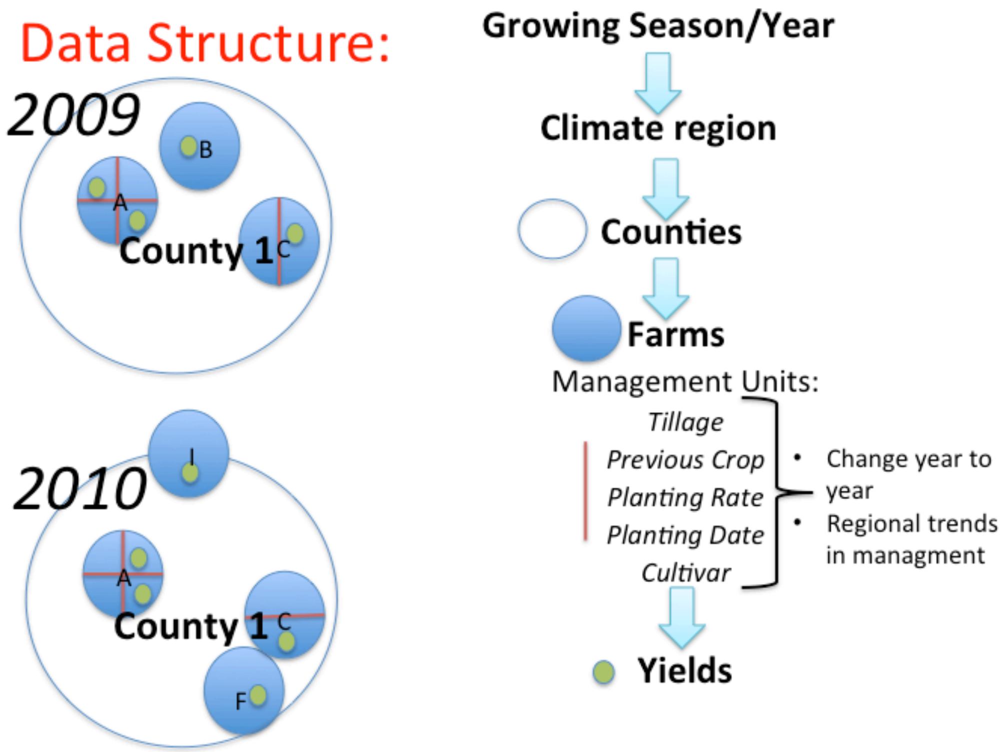

Figure 2.6: Structure of the NCGA irrigated Yield Contest data. Within a given county ("County 1"), different farms (blue circles) submit yields (green circles) in different years. Within a farm, yields (green cirlces) are submitted on different plots with different management treatments (red lines in blue circles). Some farms span multiple counties. Individual farms will submit multiple yield values from fields under different management. Farms will submit yield values with altered management from year to year.

A mixed effects model is one that contains both fixed and random effects (or variance components). Fixed effects are the traditional terms in a linear regression model; predictor variables are regressed against response variables so that discrete relationships can be modeled. Random effects adjust for population-level variables that are known to have a significant, but not explicitly defined, relationship with variance in the response variable and provide a power-preserving alternative to sub-setting data in situations where pseudoreplication from violation of independence assumptions would otherwise confound results.

We analyzed the data using linear mixed effects models (LMM) built with the *lme4* package in R (Bates *et al*., 2014). Random effects terms were introduced to allow the model to be adjusted for spatial variability (with the nearest weather station serving as a proxy for spatial yield variability), inter-farm variability (expressed as farm ID), inter-annual variability (expressed by including year of entry as a categorical variable), and genetic variability (expressed by cultivar). All random effects (location, farm, year, and cultivar) were determined to be significant using restricted estimate maximum likelihood (REML) ratio testing, as outlined in the model selection protocol in Zuur *et al*. (2009).

To prevent model scaling issues and allow for comparison of coefficients, normally distributed climate variables (radiation, average maximum temperature, average night temperature) as well as management variables (planting rate, planting date, cultivar GDD to maturity) were standardized. For the TT, NT, and KDD variables, zeros signify absence of heat stress and have unique meaning in regression analysis. These variables were log-transformed with zeros retained as zeros (McCune *et al*., 2002) using the logW0 function of the elmR package.

Farmer reported tillage was re-categorized into two categories (Conventional, Minimum/Strip-till). Previous crop was re-categorized into three categories (Corn, Soy/Beans, Other). Because of a data entry error with planting dates, 2011 planting dates were estimated by using the planting date at the Agricultural Experiment Station yield trial location nearest to the contest entry.

A full model (Zuur *et al*., 20009) was created that contained all management factors (planting rate, planting date, previous crop, tillage, and cultivar GDD to maturity), as well as year as a continuous variable (to test for yield trends), as fixed effects. All pairwise interactions between these factors were also inserted into the full model. Backwards selection using maximum likelihood (ML) ratio testing was done to identify and eliminate any non-significant interactions and terms at $\alpha = 0.01$ (Zuur *et al.* 2009). The resulting "management impacts" model, hereafter called the "base" model, was used as the null model in testing for climate variable significance.

2.5.2 Growing season analysis

First, climate variables (TT30, TT32, TT34, TT36, KDD, KDD32, KDD 34, AvgNT, NT20, NT22, NT24, NT26, RAD, VPD) which had been calculated over the entire growing season (again, duration defined uniquely for each cultivar/planting date/climate combination) were introduced to the model one at a time and compared to the "base" model to test for significance of yield impact using log-likelihood ratio testing. The KDD indices were also evaluated using modeled canopy temperature (Section 2.4.4)

Models were compared using Akaike Information Criterion (AIC) relative to that of the "base" model (the model that only including management interactions) (Zuur *et al.*, 2009). AIC is a useful criterion in this application because it evaluates model fit while giving a penalty for over fitting the model. Test models (models including climate factors) which caused a more than three point reduction over the base model were considered to be improved; models which caused a more than ten point reduction in AIC over the base model were considered to be significantly improved. To provide a relative metric for model fit, R^2 was calculated for all models using the method for defining conditional and marginal R^2 in linear mixed models proposed by Nakagawa and Schielzeth (2013).

2.5.3 Growth development phase analysis

We also explored the impact of climate during each of the delineated growth development phases. Initially, all growth development phase by climate variable individual combinations were inserted into the model one at a time and compared to the "base" model using log-likelihood ratio testing, in the same manner as was done for the "growing season" combinations.

A model was built to look at interactions maize yield response to temperatures based on when the temperatures occurred in maize phenologic development. Since as the duration of the growth development phases were modeled using GDD 34°C/8°C (or GDD with an upper limit of 34°C and a lower limit of 8°C), looking only at temperatures above 34°C allowed us to isolate potential temperature stress impacts independent of accelerated development rates, which would have already been captured as an artifact of our modeling process in the cumulative radiation index. Radiation was also selected to test for three reasons: 1) its orthogonal orientation to temperature in the irrigated climate biplot (Section 3.2) suggests that it can add dimensionality within the correlation structure of the climate data and 2) radiation gives us insight into a specific mechanism of heat-induced yield response (accelerated phenologic development).

A model was constructed with early growth radiation and TT34, sensitive period radiation and TT34, and grain-fill radiation and TT34 in balanced factorial design. In other words, we tested whether early growth exposure to high temperature significantly modified yield response to temperature later in the growing season, in addition to whether exposure to high temperature during any growth development phase had any relationship with maize yields once the beneficial response to radiation (which is correlated with high temperatures) had been accounted for, and whether yield response to radiation was in any way modified by high temperatures. Non-significant terms and interactions were eliminated using the model selection algorithm outlined in Zuur *et al.* (2009). Prior to including multiple climate variables in a single model, correlation of predictor variables was evaluated by fitting a full linear model (with no random effects) and testing the variance inflation factor (VIF) of the full model. No VIFs were found that were greater than 2.5.

2.5.4 Variance component analysis

The amount of inter-annual and location-based variability in yields explained by including a climate variable (or set of climate variables) in the model was evaluated by subtracting the year-level and location-level variance components from a fitted model from those corresponding components in the base model, and calculating the percent reduction in those variance components, as outlined in Bryk and Raudenbush (1992). To determine partitioning of yield variance to individual fixed effects, a hybrid of the Bryk and Raudenbush (1992) and Nakagawa and Schielzeth (2013) methods were employed. Fixed effects were partitioned into groups based on interaction terms; for example planting rate, panting date, and planting rate by planting date were one group; radiation, temperature and radiation by temperature were another group. If a fixed effect was not included in any interaction terms (for example, Cultivar GDD to maturity), it was the only member in its effect "group." These groups of fixed effects were inserted into the null model (one with only random effects), one group at a time. Then the fixed effects level variance (Nakagawa and Schielzeth, 2013) was determined for this test model by calculating the standard deviation of the product of the effect estimate (or vector of effect estimates) and the corresponding elements of the model design matrix. These "fixed effects level" yield variance terms were compared to the variance explained by model random effects as an indicator of relative yield influence of all model effects.

2.5.5 Adaptive management: climate/management interactions

To test for climate by management interactions, the model selection process outlined above was replicated on a "full" model containing all significant management variables and climate interactions identified in the base model, early-growth radiation and TT34, sensitive-period radiation and TT34, and grain-fill radiation and TT34 and all possible interactions (between climate and management variables) in full factorial design. The results of this model are presented in detail in Appendix C. The resulting model was considered improved based on a four point reduction in AIC, but had an increasing Bayesian Information Criteria (BIC), relative to the climate-only model (Section 2.5.4). BIC is a model selection criteria which is very similar to the AIC, but has a more conservative penalty imposed for additional model parameters. Increased BIC score may suggest model over-fitting, and model should not be used to project outside of the current range of data points.

2.5.6 Adaptive management: climate/cultivar interactions

To test cultivar interactions with climate variables, the yield contest data set was subset to include only those entries that represented popular cultivars (defined here as cultivars with more than ten contest entries). "Cultivar" was then included in the base model as a fixed effect instead of a random effect, and cultivar GDD to maturity was removed as a fixed effect. Early growth radiation and TT34, sensitive period radiation and TT34, and grain-fill radiation and TT34, and all possible interactions between climate variables and cultivar were included in the model in full factorial design. Non-significant interaction terms were removed through backwards elimination using log-likelihood ratio testing. The resulting model summary is Appendix D. Though all climate/cultivar interaction terms discussed were considered significant based on ML ratio testing, the model discussed has higher AIC and BIC scores than a comparable model built on the subsetted data using cultivar as a random effect.

2.5.7 Model validation

Model residuals were plotted against predicted variables to test for heteroskedasticity and model fit. Residuals were plotted spatially and variogram models constructed to test for spatial autocorrelation of model residuals (Figure 3.11), specifically those that would be trending along climate gradients. Fixed effects in the primary models, along with random effects structure describing location and farm ID nested in location were found to be sufficient to describe any spatial structure in the irrigated yield contest data.

3 RESULTS AND DISCUSSION

3.1 YIELD DATA OVERVIEW

Between 2005 and 2012, there was significant variability in temperature in the states of Kansas, Missouri, and Nebraska; yet with initial data visualization, the relationship between irrigated yields and this temperature variability remains unclear. The average growing season temperature between all years in our irrigated study area was 21.1°C (+/- 1.9°C), with maximum observed growing season temperatures ranging from 33.5°C to 43.9°C. The year of 2009 had the coolest growing season temperatures on average, with a mean growing season temperature of 18.7 (+/- 1.8°C). The 2012 growing season was the warmest (mean temperature 22.6°C, +/- 1°C), yet both of these years saw irrigated yield contest entries that were significantly above average (Figure 2.3). Radiation also varied over the study area, with average seasonal cumulative solar radiation of 2933 MJ/m^2 (+/- 306 MJ/m^2) varying by location and between years. Figure 3.1 shows the distribution of yield data over the study period in relation to average seasonal high temperature (top) and cumulative seasonal radiation (bottom).

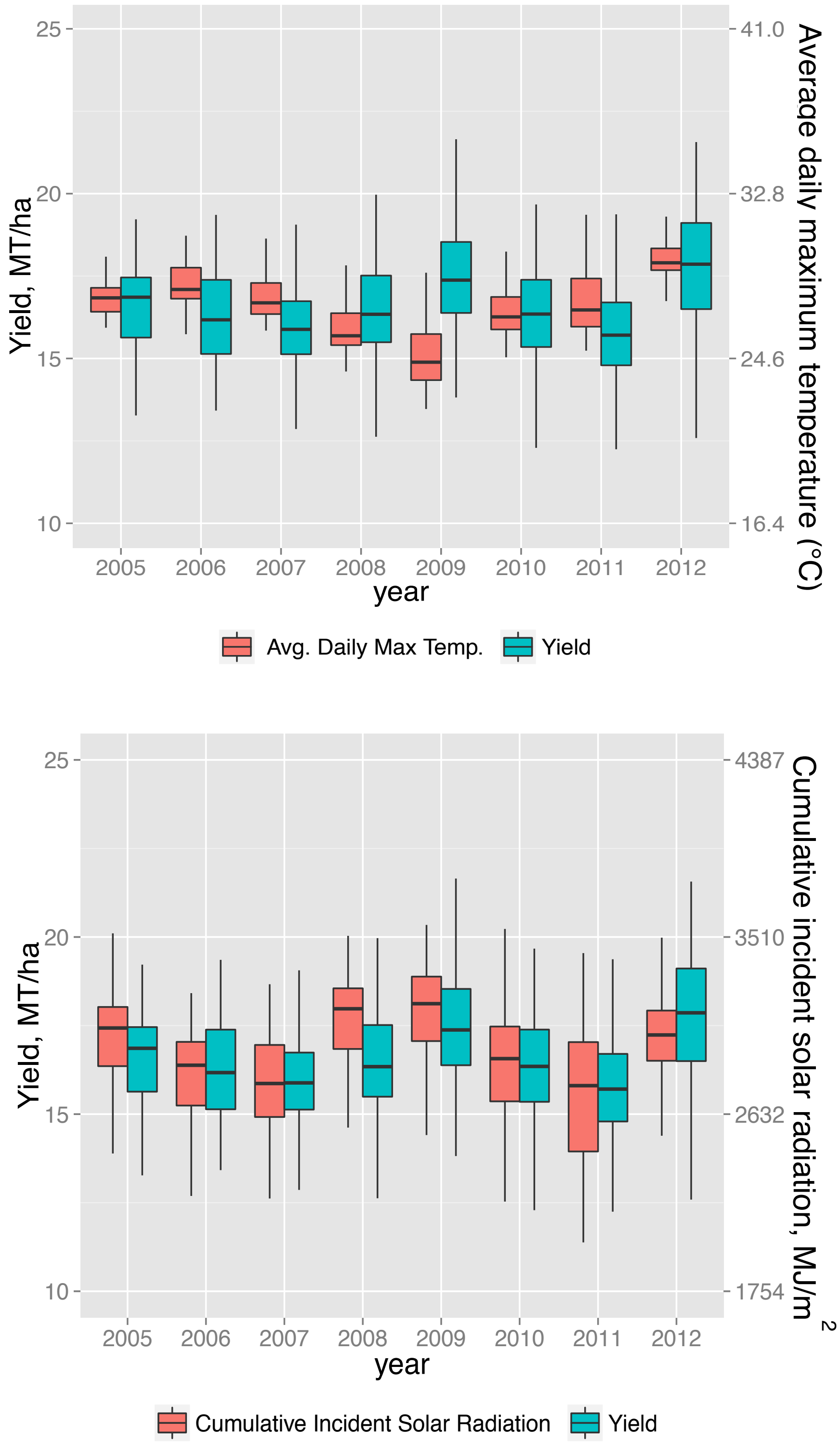

Figure 3.1: Annual irrigated yields compared to average seasonal daily maximum temperature (°C, top) and seasonal cumulative incident solar radiation (MJ/m^2, bottom). Box represents one standard deviation from the mean, and whisker represents full range of the data.

The years with highest irrigated yields, 2009 and 2012, were also the years with the lowest and highest average growing season air temperatures, respectively. In fact, extreme heat and drought conditions in the US Corn Belt in 2012 have been analyzed as an analogue to a future climate change scenario impacts on maize cropping systems (Chung *et al*. 2014; Gbegbelegbe *et al*., 2014), yet we saw our highest mean irrigated yields during this year. In contrast, years with above-average cumulative incident solar radiation tended to have above-average yields (2009 and 2012), and years with below-average cumulative radiation tended to have below average yields (2007 and 2011). Because cumulative incident solar radiation was calculated over a period defined with thermal time, low growing season temperatures increases the length of the growing season, increasing the number of days where incident solar radiation is tallied (as is likely the case with 2009 cumulative radiation values). High cumulative incident solar radiation values in 2012 were likely due to low levels of cloud cover.

Though temperature follows a strong latitudinal gradient, with higher temperatures in the southwest portion of the study region than in the north, there is no obvious spatial trend in yields. Figure 3.2 shows the distribution of yield values over the study area with a backdrop of KDD distributions in 2009 (top) and 2012 (bottom) as the coolest and warmest years in the study period, respectively. Though there is high KDD accumulation in southern Kansas in 2012, we also see high yields.

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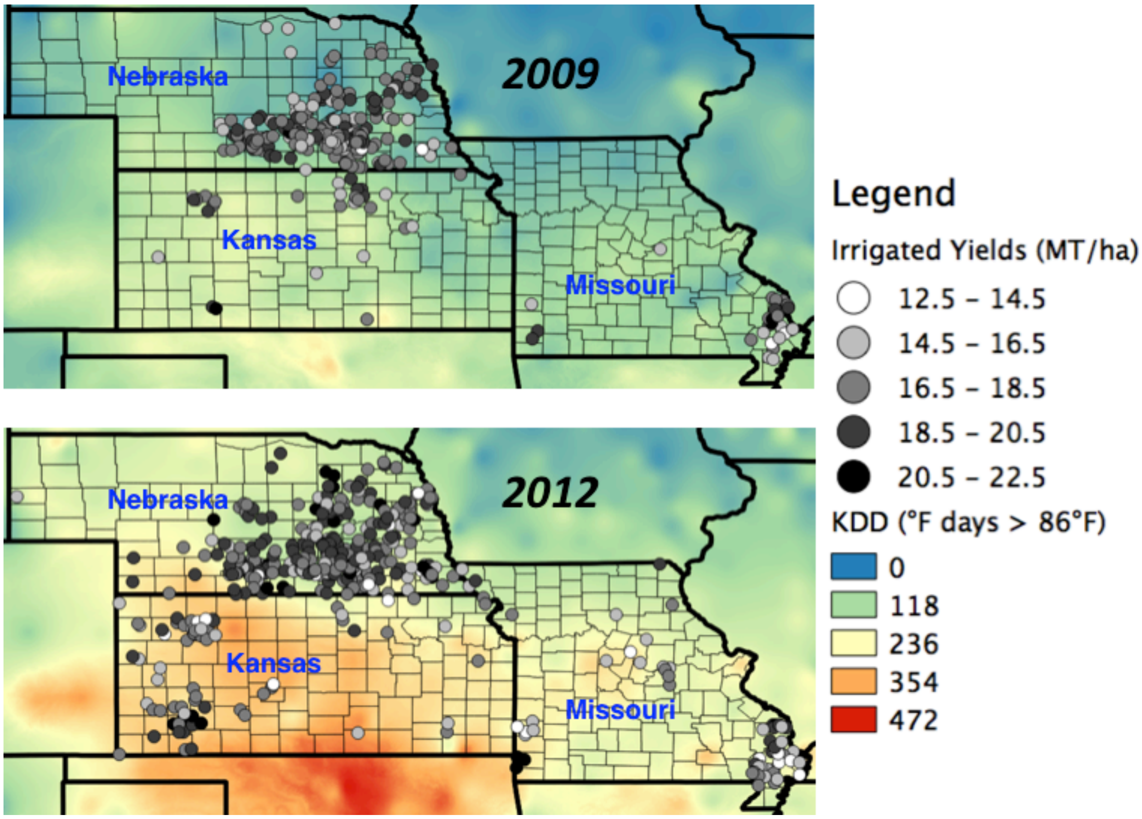

Figure 3.2: Spatial distribution of NCGA irrigated yields and growing season KDD (°F-days > 86°F) in Kansas, Missouri, and Nebraska in 2009 (above) and 2012 (below). Circles represent yield values, randomly distributed within associated county. Color scale on circles corresponds to relative yield.

3.2 CLIMATE DATA OVERVIEW

As many climate variables were correlated, principal component analysis (PCA) including all climate variables calculated over the entire growing season was performed using the "prcomp" function in R (R core team, 2014). The PCA biplot (Figure 3.3) was run using ggbiplot in the package ggplot2 in R (Wickham, 2009), and gives interesting insight into the structure of the climate data. A PCA biplot (Figure 3.3) is a display of the data in terms of covariance of predictor variables; in this case all of our climate variables. The horizontal axis, representing PC2, is completely uncorrelated with PC1, but represents the dimension of second-most correlation. The arrows represent the direction and magnitude of climate variables with regard to PC1 and PC2. The longer the arrow, the more correlated the corresponding explanatory variable is with the principal component axis of the vector direction. The biplot is also useful because it allows us to visualize where the data points, in this case categorized yield values, fall within the correlation structure of our climate variables.

With our irrigated contest entries, we do not see much specific grouping of yield levels (very low, low, high, or very high) in the principal component space of the climate variables. Very high yields are > 1.5 sd above the mean yield, high yields are between the mean and +1.5 sd from the mean, low yields are between the mean and -1.5 sd from the mean, very low yields are < 1.5 sd below the mean. Predictably, our daytime temperature indices (TT30, TT32, TT34, TT36, KDD, KDD32, KDD34) are very tightly grouped together (canopy temperature indices omitted for graphical clarity). VPD and precipitation show a very strong inverse correlation, though the orientation of these variables in relation to the yield values is, if anything, contrary to what would be expected. Though there does not appear to be strong separation of yield values within the principle component space, the grouping of very high yields appears to fall in the direction of increasing VPD, even though recent research has indicated that high VPDs have strong, negative impact on yields in rainfed maize (Urban *et al*., 2015; Lobell *et al.*, 2013; Roberts *et* al., 2013).

Night temperature variables are grouped along the same plane as daytime temperature variables, though it seems that increasing the temperature threshold night temperature indices brings us closer to the primary explanatory plane in the covariance structure, but further from the vector direction of the lower yield points. Average night temperature and radiation show a strong inverse correlation.

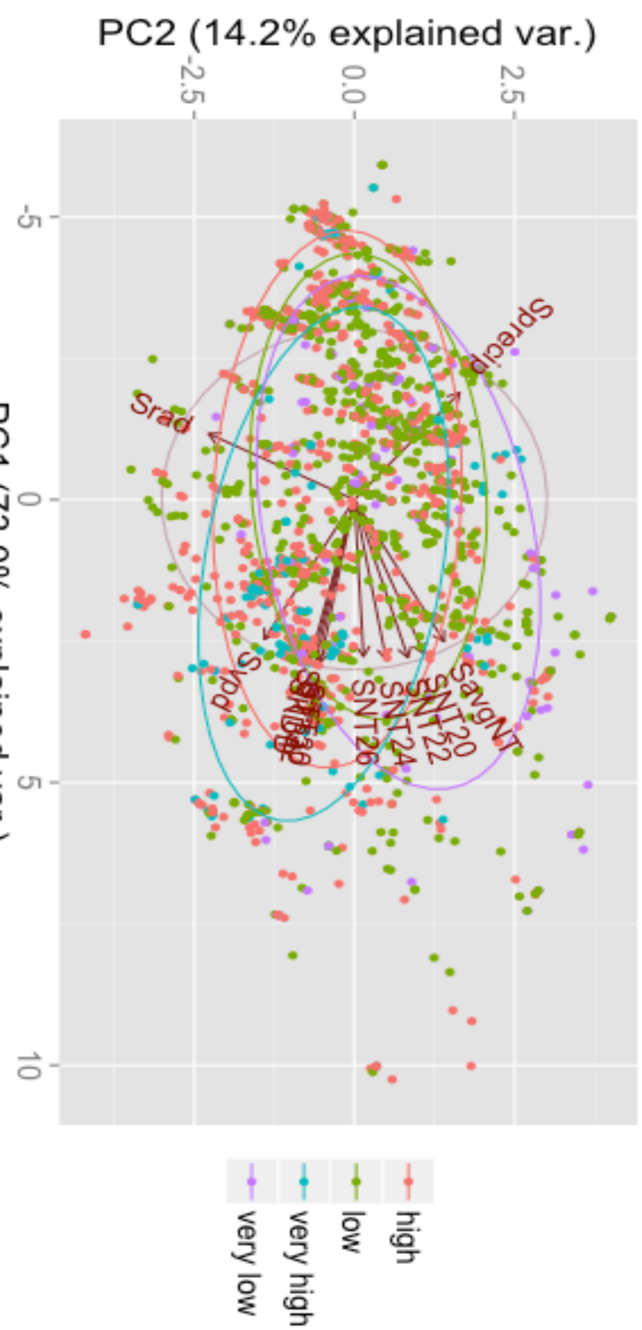

Figure 3.3: PCA Biplot of seasonal climate variables. Color gradient for irrigated yields classified into "very low" (more than 1 sd below the mean), "low" (between the mean and 1 sd below the mean), high (from the mean to 1 sd above the mean), and "very high" (greater than 1 sd above the mean). The "S" prefix indicates that climate variables were calculated over cultivar-specific thermal time defined growing season (planting date until maturity).

Our temperature variables are highly correlated with PC1, and radiation is highly correlated with PC2, therefore PC1 is the proxy for temperature type climate variables, and PC2 is the proxy for radiation type variables. Together, PC1 and PC2 explain 87.2% of the variability in all seasonal climate variables examined.

As temperature is strongly correlated with the dimension of highest explanatory power for all of our climate indices, we see evidence for why it may be so difficult to project yield response based on air temperature. If air temperature explains the majority of climate variability in a given climate system, statistical regression could relate air temperature to many different mechanisms of climate impact. Most notably, temperature can pick up on moisture stress (precipitation being inversely correlated to temperature). So even though in the data set used for model fitting there was a strong relationship between maize yields and temperature, extrapolating from this relationship can be problematic. The temperature-associated yield response would likely be describing a complex interaction between the crop and multiple climate variables; and the temperature association itself would likely be indicative of the fact that air temperature explained a significant amount of variability in a climate system. It does not indicate that yields respond strongly to air temperatures per se. Increasing air temperature with climate change would most likely alter the correlation structure between temperature and other climate variables, such as precipitation, which have discrete relationships with yield physiology. The coefficient which links yield to climate stress (as indexed by temperature) would no longer be valid in this altered climate system. Correlation of climate variables in observational data sets make mechanistic analysis of climate-crop interactions very difficult.

Though factor reduction through principal component analysis appears to be a viable course of action for regression analysis with this multidimensional data set, it was decided that working with artificial variables would limit the applicability of conclusions from this study. Climate variables, such as radiation, temperature, and VPD can be measured or modeled in a more or less standardized way, but the correlation structure between these climate variables is spatially and temporally explicit (Fovell and Fovell, 2013). Therefore, identifying yield regression estimates from measurable variables increases the context in which those estimates can be interpreted.

The PCA biplot is included here for two reasons. First, it provides important insight into the structure of the data, and to a certain extent can be looked at as a result in and of itself. As above, it also highlights potential limits of our analysis due to the fact that we had to select certain climate variables. There is more information contained in this multi-dimensional data set than we were able to process with linear regression. For example, we chose to look at cumulative radiation as a proxy for night temperature. Though we were unable to identify an impact of night temperature independent of radiation in our regression analysis (and certainly, evidence for reduced radiation being the mechanism for yield decline with increasing night temperatures is strong), the irrigated PCA biplot indicates that important information might be obscured in the correlation structure between the two variables. If there are any direct night temperature impacts on maize yield formation, such as from increased night respiration, a controlled environment where night temperature can be adjusted independent of radiation might be necessary to adequately characterize those impacts. This would be especially true if such explicit night temperature yield impacts were low-magnitude relative to yield impacts of night temperature-correlated climate variables such as radiation.

3.3 BASE MODEL: MANAGEMENT STRUCTURE

As we were interested in evaluating the magnitude of climate impacts, specifically with regards to response magnitude of other sources of yield variability, we wanted to make sure that we were using data available to us from the NGCA to characterize sources of yield variability from management variables. We were able to explain a good deal of yield variability just by looking at management. Appendix A shows the "model summary" print out from the *lmer* function of lme4 in R (Bates *et al*., 2014). Irrigated yields were significantly related to previous crop (Chisq(2)=11.3, p=3.5e-03); yields from contest entries where soy beans had been planted as a previous crop saw a 0.23 MT/ha increase (+/- 0.07 MT/ha) in yields over contest entries where corn had been planted in the previous season. Longer maturity class cultivars were significantly associated with a yield gain of 0.14 MT/ha (+/- 0.05 MT/ha) for every 100 GDD 86°F/50°F increase in thermal time needed for cultivar to reach maturity. There was quite a bit of experimentation in management in yield contest entries, and the range of reported planting rates was highly variable, ranging from 64 to 118 thousand seeds planted per hectare. Within this range, which in many cases exceeds company recommendations for optimal planting density of cultivars used, we saw a significant linear relationship with yields, with a 0.50 MT/ha yield increase (+/- 0.04 MT/ha) expected for every 7,250 seeds/ha increase in planting rate (though there are strong theoretical restrictions to extrapolating from this this trend beyond the observed range of planting rates).

Additionally, we saw that yield response to planting rate was modified by planting date. Figure 3.4 shows a detail of this interaction term using a least square means' interaction plot, or lsmip (Lenth, 2004) . Very low planting rates were associated with a yield increase from planting later in the growing season (increasing planting dates), whereas low planting rates were associated with a yield decline when they were practiced in conjunction with early planting dates. In contrast, seeding at a high rate was associated with a yield decline if the crop was planted late. But if you planted early, the benefit of high planting rates becomes particularly dramatic. Higher density plantings were associated with a significant yield gain when seeding occurred early in the growing season. Since we don't know what the resulting plant density was from these seeding rates, it is possible that higher seeding helped to buffer against reduced germination rates from unfavorable early-season conditions. For extremely high-density seeding rates that were planted later in the growing season, the inverse appeared to be true, perhaps indicating that increased germination rates from later-season seeding would lead to yield- detrimental competition in plant stands.

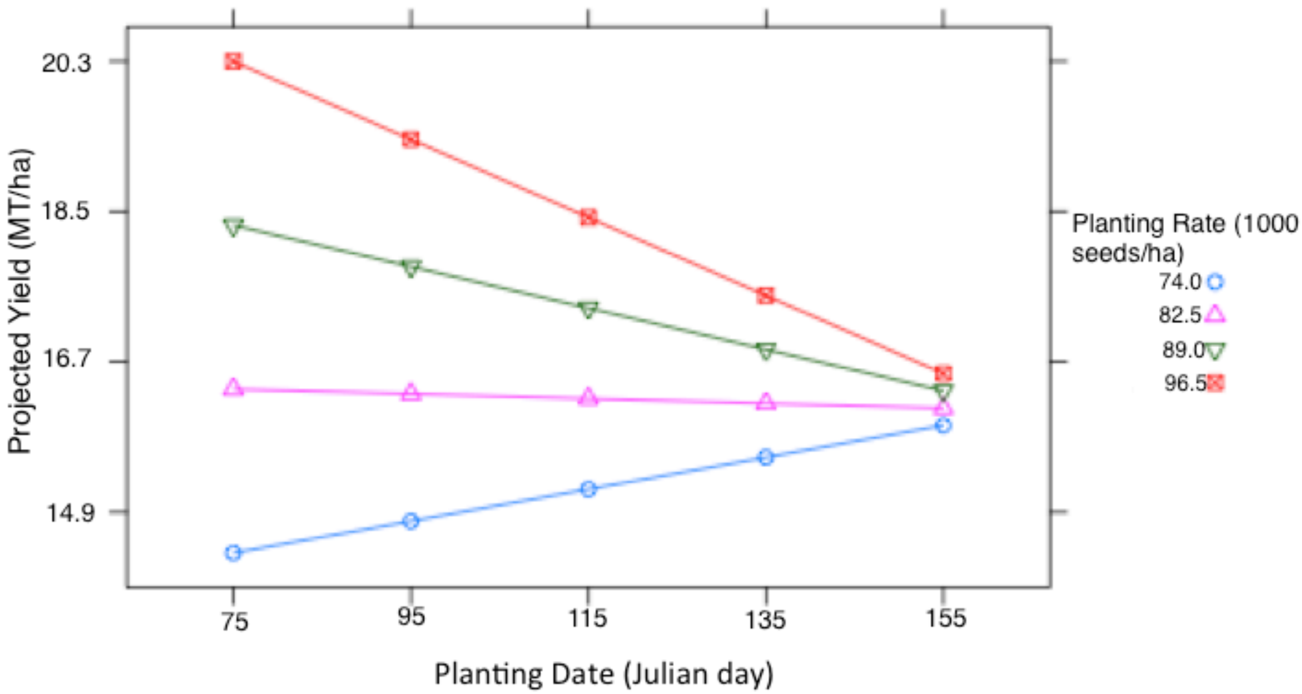

Figure 3.4: Yield response (y axis) to planting date (x axis), with lines corresponding to different planting rates. .

In our base model, a large amount of our random-effects yield variance is partitioned to farm-level variance (28%). We would expect this random effect to capture yield variance generated by any differences in management (such as fertility, irrigation, equipment), soils, or microclimate which are not parameterized as fixed effects. Location level variance, or yield variance due to spatial trends over the entire study area, explains only a very small amount (6%) of random-effects yield variance. About 15% of our yield variance appears to be due to inter-annual fluctuations in mean yield. Location-level and inter-annual variances are of particular importance to this analysis, because we expect to see regional and inter-annual variation in our climate variables. Our final random effect, cultivar, explained about 7.5% of our random-effects yield variance (See Figure 3.5) The remaining residual variance (43%) cannot be explained by any of our significant management fixed effects or random effects.

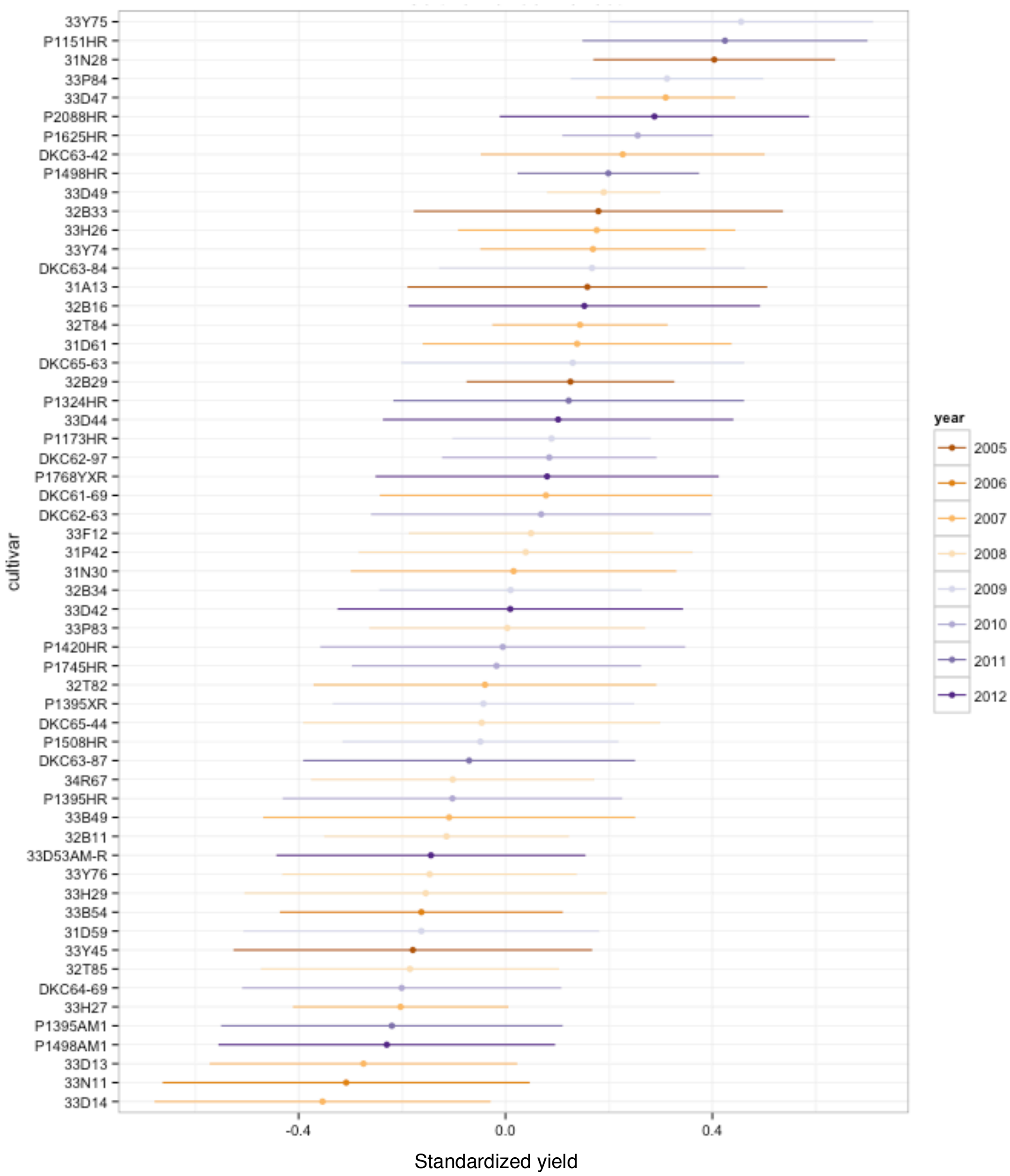

Figure 3.5 : Intercept shift (in units of standardized yield, with 1sd = 1.76 MT/ha) associated with popular cultivars in "cultivar" random effect in base model. Bar represents a 95% confidence interval. Color scale represents first year that cultivar was introduced in the data set

While our data set showed significant inter-annual variability in mean yield between years, again we did not observe a significant yield trend in the data set (p=0.40). This is advantageous, as un-parameterized yield variability estimated by including a linear trend for yield increases over time in previous econometric/statistical models has strongly influenced the results (Lobell *et al.*, 2003; Urban *et al.*, 2012). Figure 3.5 illustrates this lack of yield trend in terms of yield gain associated with cultivar. This figure shows the intercept shift associated with random effect, with a 95% confidence interval, for commonly represented cultivars. Color scale indicates year the cultivar was introduced in our data set. Cultivars prefixed with a "DK" are DeKalb brand cultivars; all other represented here are Pioneer brand. There does not appear to be any strong trend towards increasing yields based on when the cultivar was introduced into the data set.

3.4 GROWING SEASON ANALYSIS

Daytime temperature stress indices, including KDD (or cumulative degree-days over 29^{o} C), and cumulative degree-hours over 30^{o} C, 32^{o} C, 34^{o} C, and 36^{o} C, were calculated using air temperature and modeled canopy temperature (Table 2.2) for the entire growing season. None of these daytime temperature stress indices were significantly related to yields when they were calculated over the growing season (Table 3.1). In addition, vapor pressure deficit (vpd) was not significantly related to irrigated yields during the entire growing season (p=0.53).

*Table 3.1: Yield response to seasonal climate indices. Estimate represents change in yield (standardized, where 1 sd = 1.76 MT/ha) per change in unit response variable. "KDD", "TT", and "NT" indices have been log-transformed with zeros retained; "AvgNT," "RAD," and "VPD" have been standardized. For the "Significance Level," * is significant at α = 0.1, ** is significant at α = 0.05, *** is significant at α = 0.01.*

Variable	Estimate	Std. Error	p-value	AIC	Significance Level
base	model without climate indices			4419	
KDD	0.077	0.089	0.39	4420	
KDD32	-0.015	0.038	0.70	4421	
KDD34	-0.029	0.032	0.37	4420	
Canopy T KDD	-0.027	0.108	0.80	4421	
Canopy T KDD32	0.002	0.031	0.94	4421	
Canopy T KDD34	-0.011	0.013	0.36	4420	
TT30	0.031	0.056	0.58	4421	
TT32	0.022	0.038	0.56	4421	
TT34	0.002	0.016	0.89	4421	
TT36	0.005	0.011	0.67	4421	
NT20	-0.149	0.034	2.1E-05	4403	***
NT22	-0.134	0.033	7.4E-05	4405	***
NT24	-0.120	0.032	2.4E-04	4407	***
NT26	-0.100	0.031	1.5E-03	4411	***
AvgNT	-0.121	0.032	2.5E-04	4407	***
RAD	0.121	0.026	5.4E-06	4401	***
VPD	0.043	0.075	0.57	4421	

Temperature stress indices calculated from modeled daily maximum canopy temperature were also not significantly related to irrigated yields. Figure 3.6 shows the difference in growing season KDD calculated from air temperature and KDD calculated from modeled maximum daily canopy temperatures of irrigated maize. The line shows a 1:1 relationship. Growing season KDD under irrigated conditions remains significantly below what would have been calculated from air temperature measurements. Maximum daily canopy temperatures were consistently below maximum daily air temperatures, indicating that air temperature may not be a good proxy for heat stress in irrigated maize. Since energy from radiation will be partitioned to latent heat transfer when there is sufficient moisture in the system, irrigated canopies may not experience daily maximum air temperature.

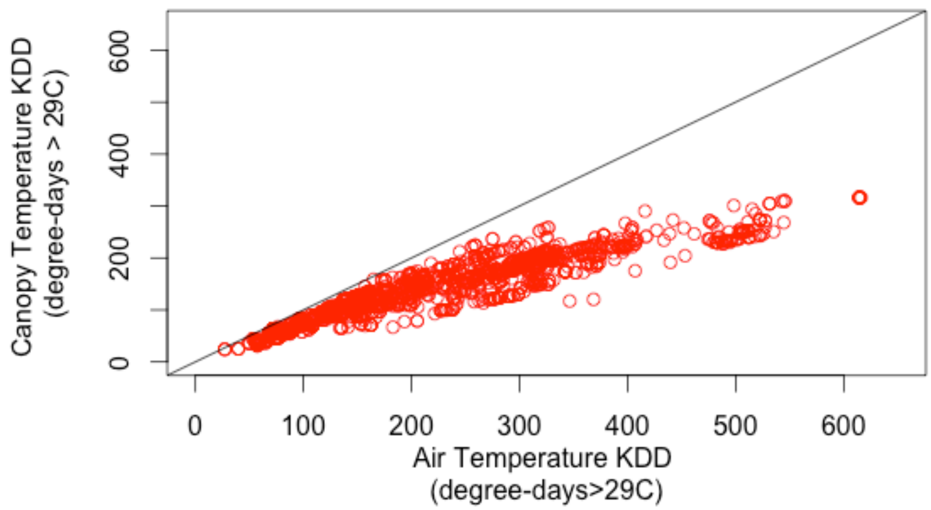

Figure 3.6: Air temperature KDD by irrigated canopy temperature KDD, with line representing a 1:1 relationship.

Cumulative radiation was correlated with increased yields (p<2.1e-06). Seasonal average night temperature was correlated with decreased yields (p= 1.3 e-04). When looked at on a standardized scale, the effect of night temperature and radiation are approximately equal in magnitude (estimates of -0.12 and 0.12, respectively). Radiation and night temperature are correlated in our data set (p-value of a bivariate fit < 2E-16, R^2=0.44; Figure 3.7). Since cloud cover has an insulating effect, increased night temperatures are associated with increased cloud cover, and increased cloud cover would in turn be associated with a decrease in incident solar radiation. Additional correlation between night temperature and radiation was captured in our data set as an artifact of having used thermal time to delineate our growth development phases. In effect, we calculated cumulative radiation per unit thermal time. Using GDD 34°C/8°C, any night temperatures above 8°C would accelerate phenological development, resulting in reduced cumulative incident solar radiation per unit thermal time. Accelerated development rates have frequently been implicated as the cause of yield declines associated with night temperature (Hatfield et al., 2014; Crafts-Brandner and Salvucci, 2002; Canterero et al., 1999; Chang, 1981), as decreased radiation leads to a decrease in photosynthate available for biomass production over the net life of the crop.

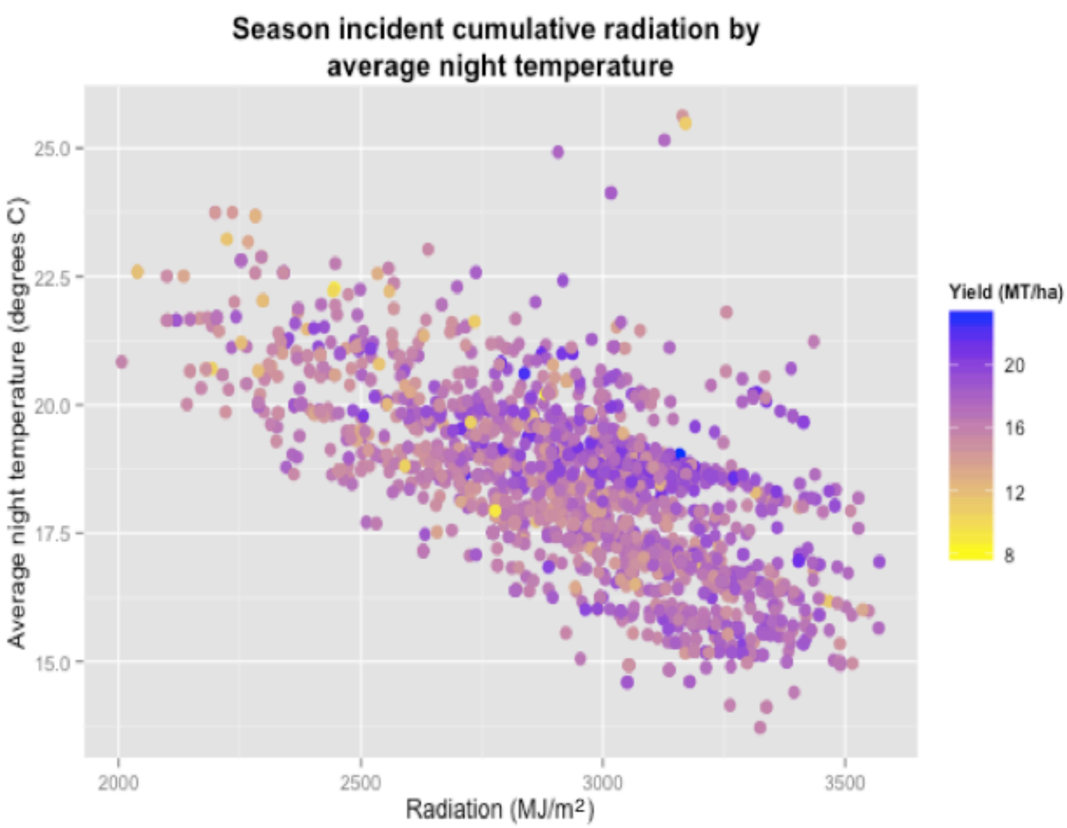

Figure 3.7: Scatterplot of seasonal average night temperature and cumulative solar radiation, with color scale to show associated irrigated yield values.

In our PCA biplot of seasonal climate variables (Figure 3.3) average night temperature and seasonal cumulative incident solar radiation are imperfectly inversely correlated, so there is some variability in climate data that cannot be explained entirely with one of the variables or the other. There are two schools of thought about mechanisms for decreased maize yields under increased night temperatures. The first, as we capture in our method of modeling the duration of our growth development periods and discussed above, is that increased night temperatures lead to accelerated development, which in turn means that there is less sunlight available for photosynthesis over the net life of the plant (Hatfield et al., 2014; Crafts-Brandner and Salvucci, 2002; Canterero et al., 1999; Chang, 1981). The second is that increased night temperature leads to increased cellular respiration, which would cause stored photosynthate to be lost as CO_2 (Gifford, 2003; Suyker *et al*., 2005).

To test whether night temperature had an impact on yields independent of radiation (as would have been indicated by increased nighttime respiration or cellular damage), night temperature and radiation were modeled simultaneously. There was no significant crossed effect between night temperature and radiation (p=0.78), and the yield impact of night temperature becomes statistically insignificant if radiation is accounted for in the model (p=0.18). Because of this, and because there does not appear to be a trend towards increasing yield loss with an increase in the night temperature threshold considered stressful (Table 3.1), our data appears to support the hypothesis that increased night temperatures are correlated with decreased maize yields due to associations with decreased cumulative incident solar radiation per unit thermal time over the growing season, either through increased development rates and/or association between high night temperatures and overcast conditions.

3.5 GROWTH DEVELOPMENT PHASE ANALYSIS

3.5.1 Climate impacts by growth development phase

Though no significant relationship between high day time temperatures and yields were seen when those temperature impacts were examined over the entire growing season, we examined whether there were specific links to yields when high temperatures were concurrent with maize growth stages, specifically during the period before and after silking ("sensitive period"), and during grain-fill. Climate stress indices by growth development phase were inputted to the model one at a time to test for significance. Table 3.2 shows the results of this analysis.

Table 3.2: Yield response to climate indices by growth development phase. . Units of "estimate" are standard deviations in yield/standard deviations in response variable (for average max temperature, average night temperature, VPD, and radiation) or standard deviations in yield/log response variable (for all KDD, TT, and NT indices). One standard deviation of yield was 1.76 MT/ha in this data set. Red text indicates a variable that was significant by a 3 point or greater reduction in AIC, blue text indicates a variable that was significant at $\alpha = 0.05$ (p-value obtained from ML ratio testing) but did not have a significant reduction in AIC.

Climate Variable	Metric	Early-growth	Sensitive	Grain-fill
Average Max T	Estimate	-0.03	0.09	-0.07
	Standard Error	0.04	0.04	0.04
	p-value	0.46	0.01	0.11
	AIC	4427.4	4421.6	4425.4
KDD	Estimate	-4.4E-03	0.08	0.08
	Standard Error	0.05	0.07	0.05
	p-value	0.93	0.25	0.08
	AIC	4427.9	4426.6	4424.9
KDD32	Estimate	0.04	0.03	-0.07
	Standard Error	0.03	0.03	0.04
	p-value	0.23	0.29	0.06
	AIC	4426.5	4426.8	4424.5
KDD34	Estimate	0.05	-0.01	-0.06
	Standard Error	0.03	0.03	0.03

	p-value	0.05	0.65	0.04
	AIC	4424.0	4427.7	4423.7
Canopy T KDD	Estimate	0.01	0.02	0.03
	Standard Error	0.06	0.07	0.04
	p-value	0.80	0.80	0.49
	AIC	4427.8	4427.8	4427.4
Canopy T KDD32	Estimate	4.4E-04	-5.5E-03	4.4E-04
	Standard Error	0.02	0.02	0.02
	p-value	0.98	0.76	0.98
	AIC	4427.9	4427.8	4427.9
Canopy T KDD34	Estimate	0.04	-0.02	-0.02
	Standard Error	0.01	0.02	0.01
	p-value	0.00	0.21	0.04
	AIC	4414.3	4426.4	4423.9
TT30	Estimate	1.2E-03	0.01	0.04
	Standard Error	0.04	0.04	0.03
	p-value	0.97	0.77	0.17
	AIC	4427.9	4427.8	4426.1
TT32	Estimate	0.01	0.02	0.02
	Standard Error	0.01	0.02	0.01
	p-value	0.47	0.40	0.16
	AIC	4427.4	4427.2	4426
TT34	Estimate	0.03	0.02	0.01
	Standard Error	0.01	0.01	0.01
	p-value	0.00	0.08	0.27
	AIC	4417.8	4424.9	4426.8
TT36	Estimate	0.02	0.01	0.01
	Standard Error	0.01	0.01	0.01
	p-value	0.11	0.65	0.16
	AIC	4425.3	4427.7	4425.9
Average Night T	Estimate	-0.02	-0.02	-0.16
	Standard Error	0.03	0.03	0.04
	p-value	0.49	0.47	1.4E-05
	AIC	4427.5	4427.4	4408.5
NT20	Estimate	0.01	-0.05	-0.17
	Standard Error	0.03	0.03	0.04
	p-value	0.67	0.12	2.9E-06
	AIC	4427.7	4425.6	4405.1
NT22	Estimate	0.02	-0.04	-0.16
	Standard Error	0.03	0.03	0.03

	p-value	0.46	0.23	0.00
	AIC	4427.4	4426.5	4404.7
NT24	Estimate	0.03	-0.03	-0.16
	Standard Error	0.03	0.03	0.03
	p-value	0.26	0.37	1.0E-06
	AIC	4426.6	4427.1	4403.5
NT26	Estimate	0.05	-0.01	-0.14
	Standard Error	0.03	0.03	0.03
	p-value	0.10	0.61	2.9E-06
	AIC	4425.2	4427.6	4405.7
VPD	Estimate	0.02	0.06	0.02
	Standard Error	0.08	0.04	0.05
	p-value	0.85	0.19	0.73
	AIC	4427.9	4426.2	4427.8
Radiation	Estimate	0.12	0.05	0.10
	Standard Error	0.03	0.03	0.03
	p-value	1.1E-05	0.08	5.0E-05
	AIC	4408.6	4424.9	4412.1

Daytime air temperature stress indices at temperature ranges typically utilized in the literature (29°C-32°C) are not significantly related to irrigated yields, even when these temperature impacts occurred during key growth development phases. Looking at modeled canopy temperature, we see that increasing canopy temperature degree-days over 34°C during early-growth were associated with a positive yield response, but that increasing degree-days over 34°C during grain-fill were associated with a slight yield decline. Conditions leading to high canopy temperatures would include concurrent high air temperatures, high radiation, and low vapor pressure deficits.

Radiation continues to have a strong positive relationship with yields, especially during early vegetative growth and grain-fill, and the negative impacts of night temperature appear strongest during grain-fill. Air temperature impacts do not seem to increase in magnitude with increasing optimal night temperature threshold. In fact, the effect sizes of the NT indices seem to decrease with higher optimum temperatures. Night temperatures are only significant during grain-fill, when photosynthate is directly partitioned into grain development, and the yield impacts related to night temperature are reduced when we look only at increasingly high night temperatures (i.e. the estimate for NT26 is of smaller magnitude than NT20). Both these things seem to support the earlier hypothesis that night temperatures are impacting yields by way of associative decreased radiation.

3.5.2 Direct temperature stress impacts

Radiation and daytime temperature stress indices are correlated in the data set, and since yield response to radiation is so strong, there is concern that radiation could be masking potential temperature stress impacts. Looking back at our PCA biplot (Figure 3.2), we also see that our temperature variables are almost perfectly correlated with PC1, and radiation is almost perfectly correlated with PC2, therefore PC1 is the proxy for temperature type climate variables, and PC2 is the proxy for radiation type variables. Together, PC1 and PC2 explain 87.2% of the variability in all seasonal climate variables. Since we are interested in dynamic plant response to high temperature, and we are also interested in monitoring for heat stress mechanisms independent of the interaction between heat, growth rates, and intercepted radiation, we must look at how climate variables experienced throughout the growing season impact yields once radiation has already been accounted for in the model. Modeling radiation and daytime temperature together has the added benefit of allowing us to capture a majority of variability in our climate data.

Using the model selection process outlined in methods Section 2.5.3, we looked at early growth radiation and TT34, sensitive period radiation and TT34, and grain-fill radiation and TT34, as well as interactions between early growth, sensitive period, and grain-fill TT34. The resulting model output can be seen in Appendix B, and is visually summarized in Figure 3.8, which shows a coefficient plot of the Radiation by TT34 model (left) with prediction-plot details illustrating crossed effects in terms of projected standardized yield impacts (right).

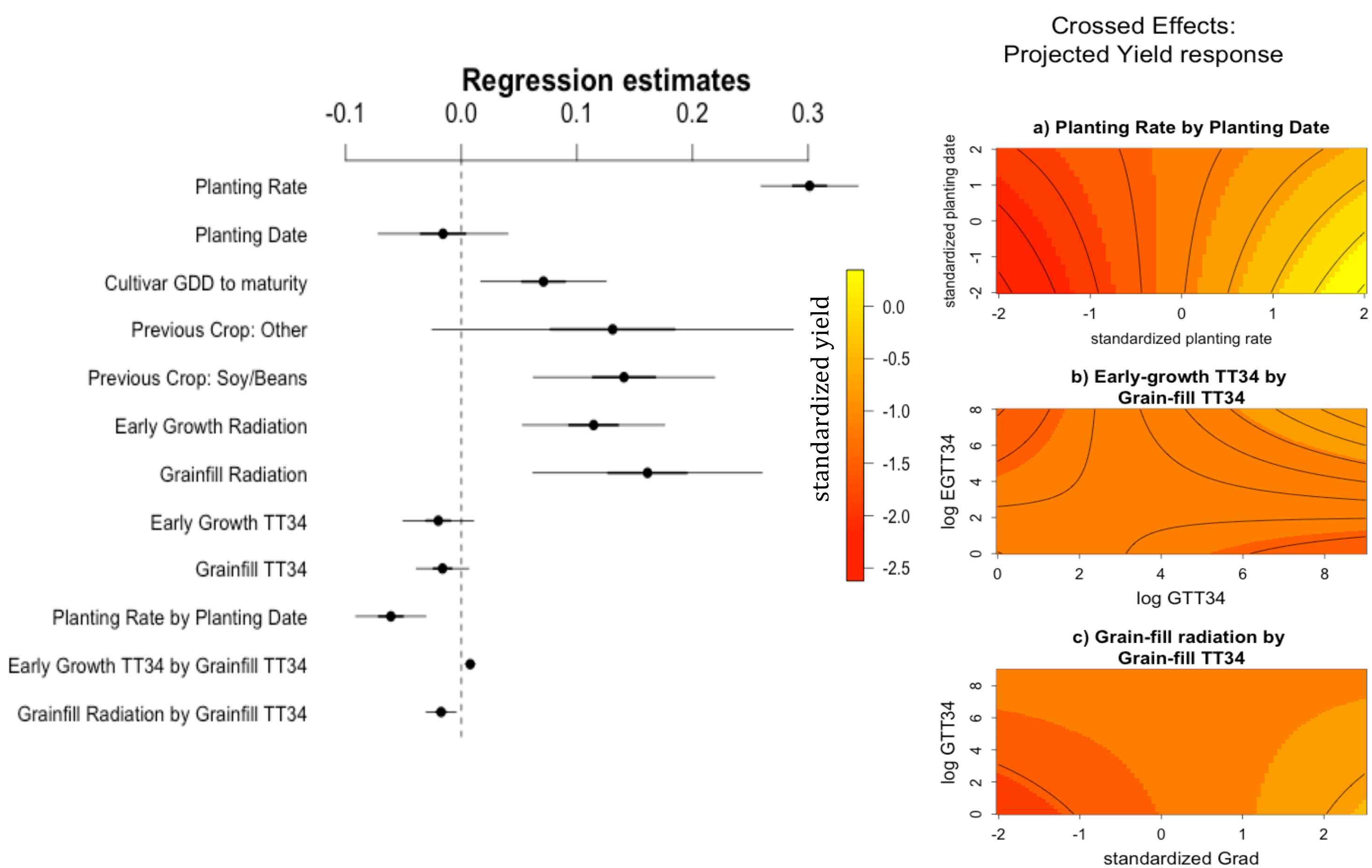

Figure 3.8 : Visual summary of radiation by TT34 model. Coefficient plot of the Radiation by TT34 model (left) with prediction-plot details illustrating crossed effects in terms of projected standardized yield impacts (right). "Regression estimates" describe the change in standard-deviations of yield (1.76 MT/ha) per standard-deviation change in predictor variable (cumulative solar radiation, planting rate, planting date, cultivar GDD to maturity), or one unit change in log-transformed TT34. Note: model has a negative intercept.

Adjusting for radiation, we see that TT34 does significantly interact with yields, but that yield response to TT34 is complex. High temperatures during grain-fill significantly reduce yield gains that would by expected from increased radiation during grain-fill (p=0.008), but yield response to grain-fill TT34 is modified by the temperature regime experienced by the crop in early growth. When high values of TT34 occurred as isolated events during either early growth or during grain-fill, we see significant negative impacts on yields. But, the interaction effect between early growth and grain-fill TT34 is significant (p=4.7e-4), and is positive. This means that if the crop experienced temperature stress (as indexed by TT34) early in the growing season, yield response to TT34 during grain-fill is positively modified. In fact, if high levels of TT34 are seen during early growth and grain-fill, the yield response is positive (See figure 3.9 for detail of this interaction).

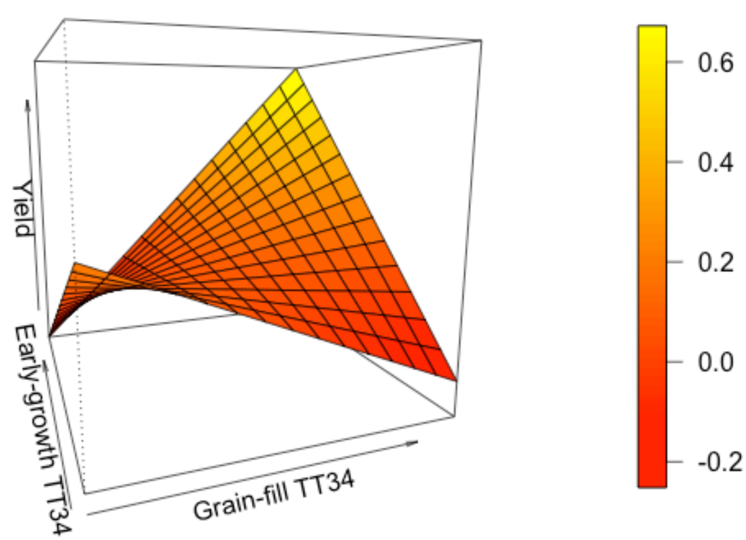

Figure 3.9: Detail of projected yield response (color scale to right is standardized yield, with 1 sd = 1.76 MT/ha) with interaction between early-growth and grain-fill TT34.

This response is consistent with evidence of potential for acquired thermo-tolerance in maize. Sung *et al.* (2003) and Kotak *et al.* (2007) outline mechanisms for temperature stress perception and transcriptional activation of heat-tolerant genes in many plants, including maize. Crafts-Brandner and Salvucci (2002) observe that net photosynthesis was reduced when maize plants were subjected to temperatures above 38°C, but that this effect was "much more severe when the temperature was increased rapidly rather than gradually." Sinsewat *et al*. (2004) identifies a strong heat-stress response in maize grown at low temperatures (25°C) when there were subjected to temperatures of 35°C, with permanent damage resulting when plants were subjected to temperatures greater than 45°C, but observe that no negative response is seen when plants grown at 41°C are subjected to sudden temperature increases, even to temperatures as high as 51°C. Cicchino *et al.* (2010) determined that the threshold temperature at which plants experience heat stress is modified by previous temperature regimes, and that the optimum temperature for the crop shifts based on agro-ecological zone, as well as between different climate-years in the same location.

Acquired thermo-tolerance, in conjunction with use of locally-adaptive cultivars and spatial variation in climate-adapted management practices, may explain why we see no detectable latitudinal trend in our yield data, even though there is a strong north-south gradient in incidence of high temperatures within our study area (see Figure 3.2).

Radiation remains significant in early growth and grain-fill. Very low levels or very high levels of TT34 during grain-fill slightly dampened yield gains due to increased cumulative radiation during grain-fill (Figure 3.8a), suggesting that moderate heat is in fact beneficial for radiation use efficiency. Once again, we see evidence in the literature that both low and high temperatures can have detrimental impacts on yield formation in maize. For example, Andrade *et al.* (1991) demonstrated a positive, linear relationship between increasing temperature and radiation use efficiency in maize. Crafts-Brandner and Salvucci (2002) show decreases in photosynthesis during temperatures in excess of 38°C (though, once again, this response depends on the previous temperature regime experienced by the plant).

Though much attention has been given to the critical role of heat stress during the period immediately before and after silking in maize as it relates to yield formation, we saw no significant relationship between high temperature (TT34) and yields when increasing TT34 occurred during the sensitive period ($Chisq(1)=0.34$, $p=0.56$). Radiation during this critical period was also not significantly related to yield ($Chisq(1)=0.42$, $p=0.52$). These results are consistent with other similar studies (Lobell *et al.,* 2013), and may reflect advances in breeding in the past half-century to improve stress tolerance around silking; including earlier silking times, reduction in anthesis to silking interval (ASI), reduction in tassel size, and reduction in number of ears per plant (Duvick, 2005).

Of the climate variables tested, radiation appears to be the most yield-limiting factor in irrigated maize production systems. A 170 MJ/m^2 increase in early-growth radiation was associated with a 0.2 MT/ha increase in yields. An additional yield boost from above-average radiation could be seen during grain-fill, where a roughly 140 MJ/m^2 increase in cumulative radiation was associated with a roughly 0.3 MT/ha increase in yields, though with extreme high temperatures we see only a very slight yield gain for twice this amount of radiation (with a 0.013 MT/ha yield increase expected for an additional 280 MJ/m^2 with the maximum observed grain-fill TT34 in our dataset). The yield-limiting impact of radiation is consistent with what would be expected of yields under ideal management, and may be reflective of the quality of the NCGA Yield Contest dataset (Monteith, 1981).

Though statistically significant, the effect sizes of early growth and grain-fill temperature on maize yields were small, suggesting that observed impacts of high temperatures in irrigated maize are of little agronomic importance under current temperature regimes in the US Corn Belt. The strongest temperature-associated yield responses were seen when 1) highest levels of early growth TT34 were followed by few or no days with temperatures over 34 degrees during grain-fill, resulting in 0.2 MT/ha yield decrease, and 2) when consistent high temperatures occurred both in early-growth and grain-fill, associated with a yield gain of up to 0.35 MT/ha. Significant management variables have much larger yield impacts. Coupling a high planting rate with an early planting date was associated with an approximately 1 MT/ha yield increase, and selection of a high or low performing cultivar can make the difference of plus or minus 0.7 MT/ha at the end of the season.

A model which includes all significant temperature and radiation impacts by critical period (marginal R^2 =0.146, conditional R^2= 0.624) explains very little yield additional yield variance compared to the growing season radiation model (marginal R^2 =0.141, conditional R^2= 0.607) (Nakagawa and Schielzeth, 2013), suggesting, again, that identified statistically significant temperature responses in yield are of little biological importance for irrigated maize.

The relative response magnitude of yield to management, as opposed to climate, can be seen more clearly by examining the amount of variance explained by each variable (Figure 3.10). Radiation and TT34 only explain a small amount of yield variance relative to other factors. Variables which have strongest impacts on yields include "Other genetics" (cultivar-associated variance which was not explained by cultivar maturity class), "Planting Rate and Planting Date" (the individual and interaction terms explaining yield response to planting date and planting rate), and "Farm-level" (or yield performance between farm level conditions not explained by other management parameters, may include fertility, soils, irrigation, etc). It is interesting to note that GDD to maturity did not have much impact on crop yields, especially relative to other genetic factors. This could be because farmers in the NGCA yield contest are already optimizing this for their location. Nearly 35% of yield variance remains unexplained by the model.

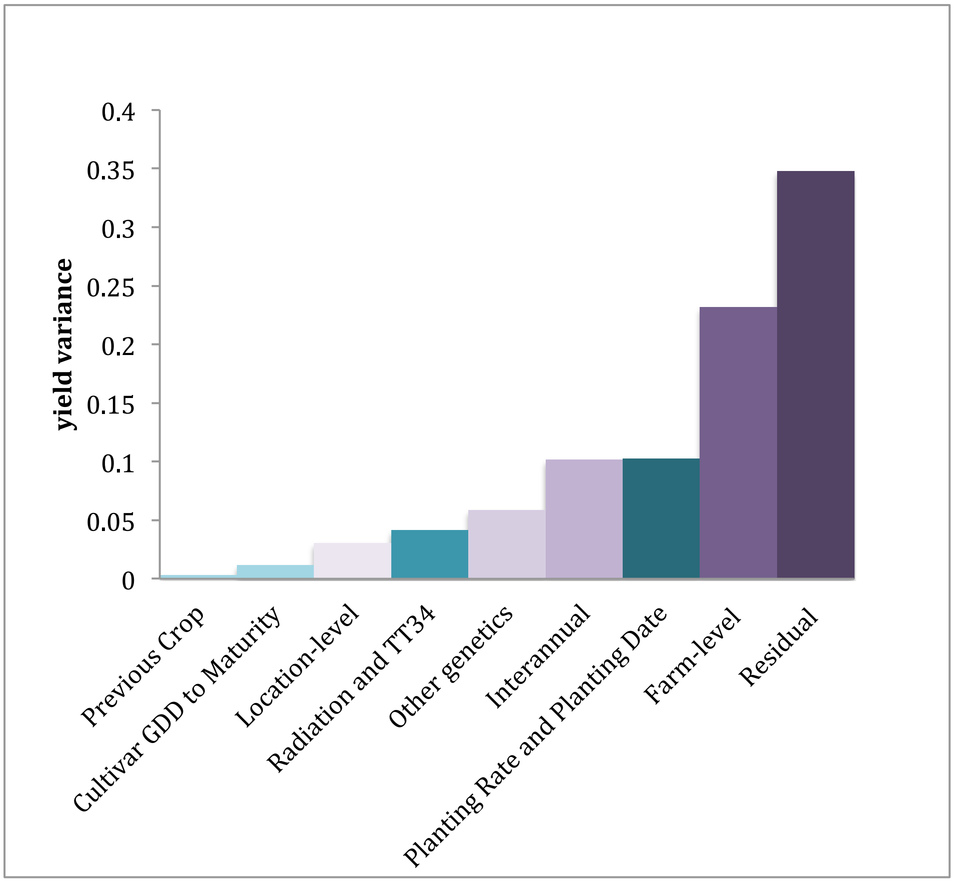

Figure 3.10: Yield variance explained by random effects (other genetics, inter-annual variance, farm-level variance, location-level variance, residual variance, all shown in purple) and fixed effects (planting rate and planting date, cultivar GDD to maturity, previous crop, radiation and TT34, calculated as fixed effects level variance from test models as detailed in methods and materials, shown in blue) for the critical period radiation and TT34 model which does not include climate by management interactions

Variables which had the largest impact on yields include "Other genetics", "Planting Rate and Planting Date", and "Farm-level". Combined, these three variables accounted for approximately 35 – 40% of the yield variance, suggesting that even on the highest-performing farms, there is significant room for yield improvements. Table 3.3 shows how addition of significant climate interactions modified variance partitioning among random effects in the model. Seeing which levels of variance were explained by addition of climate variables ("Rad and TT34" model) as fixed effects over the amount of variance explained by the “base” model, gives insight into how much inter-annual variance, location-level variance, farm-level variance, and genetic variance are explained by climate factors. Accounting for all significant radiation and temperature impacts on yields only explained 14% of original inter-annual yield variance, suggesting that in irrigated maize, 86% of inter-annual yield anomaly is due to other factors (such as pests, disease, or unanalyzed climate variables). Only 10% of cultivar performance variability can be explained by temperature interactions.

Table 3.3: Climate impacts on variance components partitioning.

	Variance explained:		
Groups	**Base Model**	**Rad and TT34:**	**% Explained by Climate**
farm-level	0.23	0.23	0.05%
cultivar	0.06	0.05	9.67%
location-level	0.05	0.03	30.29%
inter-annual	0.12	0.10	14.58%
residual	0.36	0.35	2.23%
Total variance*	0.81	0.77	5.66%

*leftover from yield variance explained by fixed effects

All radiation and climate variables, which included an interaction term which suggested acclimation to heat stress, reduced the small amount of yield variance partitioning to location by over 30%, though the amount of yield variance described by a location random effect was small to begin with (about 4%). The relationship between spatial yield distribution and evidence of acquired thermo-tolerance in maize may explain at least part of the “spatial adaptation” to heat stress observed in Butler and Huybers (2013). We then plotted our model residuals on the map of our study area to see if our model was over-predicting or under-predicting yields in any specific locations, and built a spatial variogram of those residuals to see if there was any obvious spatial trend in our data that were not characterized by our predictor variables. We saw no spatial trend in the residuals (see Figure 3.11).

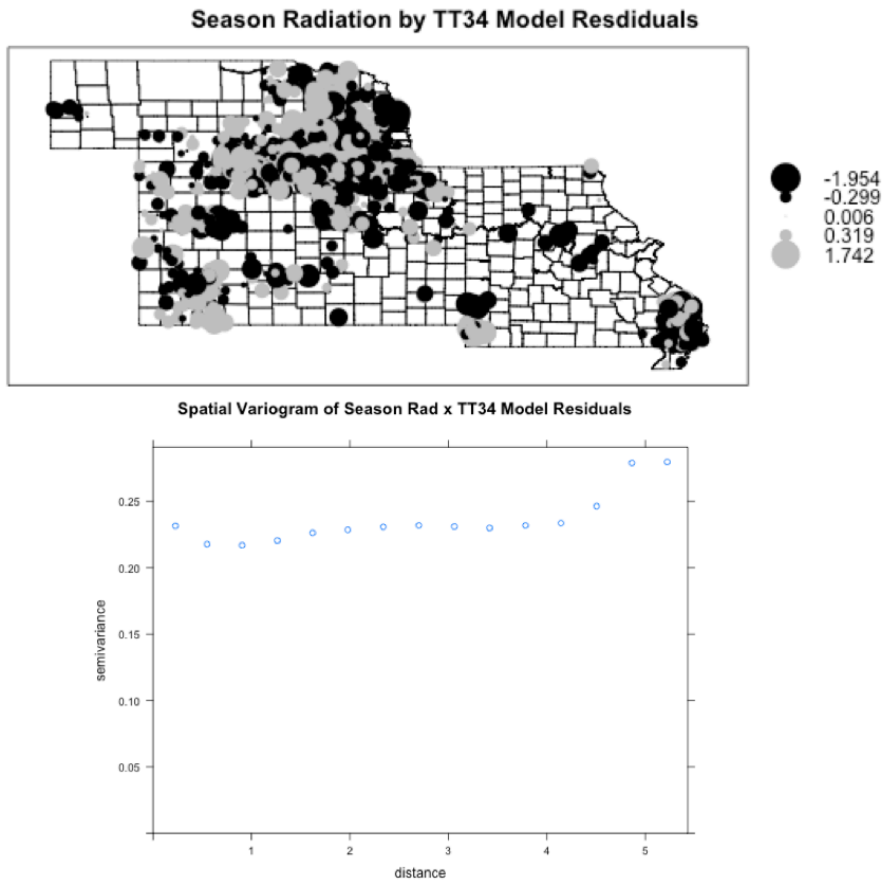

Figure 3.11: Map and spatial variogram of critical period radiation by TT34 model residuals. Circles in map (above) represent difference between projected and actual yield in units of standardized yield.

3.5.3 Climate-adaptive management

Perhaps the only question of more interest than “How will our cropping systems function in a changing climate?” is “What can we do about it?” Understanding whether significant management variables interact with crop climate response can give us insight into which management practices might be targeted for adaptation to climate stress. A model was constructed to examine significant interactions between TT34, radiation, and management variables (planting rate, planting date, and cultivar GDD to maturity). See Appendix C for model summary. (Note: significance level for this model selection process was set as alpha = 0.1)

We see that increasing the planting date is significantly associated with a decrease in the negative impact of grain-fill TT34 (p=2.7 e-04). In other words, if you delay planting, your crop will not be as susceptible to high temperatures later in the growing season. This is in agreement with the previously observed thermo-acclimation response. Later plantings would generally be associated with warmer conditions during early vegetative growth, which are then associated with a positive modification of yield response to high temperatures occurring later in the growing season.

Another significant adaptation mechanism was choosing a cultivar with a longer maturity class. Longer season cultivars were significantly associated with yield increases at higher temperatures, and appear to provide a positive buffer against temperature impacts on radiation during grain-fill. From a mechanistic point of view, selection of longer season cultivars would be expected to reduce yield losses from accelerated phenologic development under high temperatures. If more thermal time is required for the crop to reach maturity, it will spend more time growing and intercepting radiation than a shorter season cultivar, which would increase photosynthate production over the life of the plant. The fact that increasing maturity class was associated with a decrease in yield loss from high temperatures suggests that, even after adjusting for radiation, our low-magnitude temperature impacts may be related to accelerated phenologic development.

Again, the magnitude of yield response to management parameters are orders of magnitude greater than the magnitude of yield response to temperature, even as these management parameters themselves modify yield response to temperature. For this reason, we selected an “optimal management” scenario to test if the magnitude of yield response to climate could be offset by slightly optimizing from within the current range of cultural practices under ideal management in the US Corn Belt. “Typical management” includes the mean planting date, the mean planting rate, and an average-performing cultivar of the median maturity class. “Ideal management” considers a cultivar of an above-average maturity class (0.5 standard deviation above the NCGA irrigated yield contest mean planting date), a below-average planting date (0.5 standard deviation below the mean), and an above-average planting rate (0.5 standard deviation above the mean). “Reduced radiation” describes the same situation with a one standard deviation reduction in cumulative incident solar radiation during early growth, and average radiation during grain-fill, in conjunction with an assertion in the 2014 National Climate Assessment that the region can expect to see increased cloud cover early in the growing season (Schafer *et al.*, 2014).

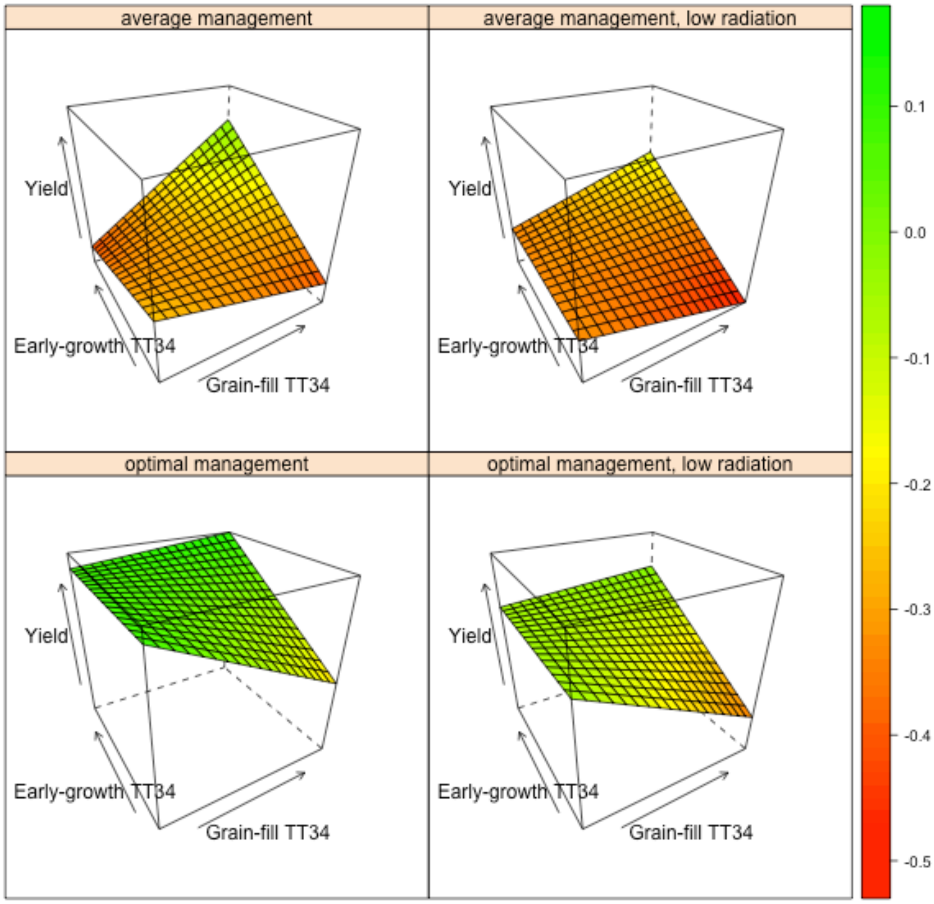

Figure 3.12: Projected yield response to high temperatures (TT34) during early-growth (y axis) and grain-fill (x axis) under typical (above) and ideal (below) management. The left two panels have average radiation, and the right two panels have "low radiation" during early growth. The z axis (color scale) represents projected yield, in units of standardized yield (sd = 1.76 MT/ha)

Highest yields are seen with "ideal" management (Figure 3.12, lower panels) when there are temperatures at the upper extreme of our data set in early-growth and average to above-average radiation throughout the growing season, while no or low heat-stress in early growth increases susceptibility to slight yield declines from high temperatures during grain-fill. The yield scale of the "ideal management" projection plots barely even intersect with the yield scale of the "typical management" projection plots, at any beneficial or detrimental level of radiation or temperature, suggesting that even slight optimizations within the range of current cultural practices in the U.S. Corn Belt is sufficient to offset any temperature-induced yield declines in irrigated maize.

3.5.4 Genetic variability in heat stress response

As the only significant temperature impacts in our irrigated maize yield data set are seen as interaction terms indicating the significance of acclimation responses to heat stress in maize (early-growth by grain-fill TT34), and since this interaction explains nearly 10% of the genetic variability in yield response with our data set (Table 3.3), we see evidence that temperature interactions with yield formation are mediated by both metabolic and genetic processes.

It has been well documented, both by global distribution of maize production, and in controlled research, that maize growth response to temperature differs between cultivars that are locally adapted to different climates (Duncan and Hesketh, 1968). Improving maize resiliency to climate extremes such as heat stress, especially during the period immediately before and after silking, has been a concerted focus of public and private maize breeding initiatives for decades (Duvick, 2005). Because of this, it was expected that different maize cultivars would have different responses to temperature stress.

The 2005-2012 NCGA irrigated classes yield contest data set contained yield values from 319 unique cultivars sourced from 26 different seed companies. While many of these were single-entry cultivars, 33 cultivars were used in ten or more contest entries. Figure 3.13 shows the distribution of yield values associated with these “popular” cultivars. The four cultivars prefixed with “DK” are DeKalb® brand cultivars, the remaining are Pioneer® brand cultivars. The data was sub-setted to include only yields from these “popular” cultivars. A model was constructed (Section 2.5.6) that looked at interactions between climate (TT34, radiation) and cultivar.

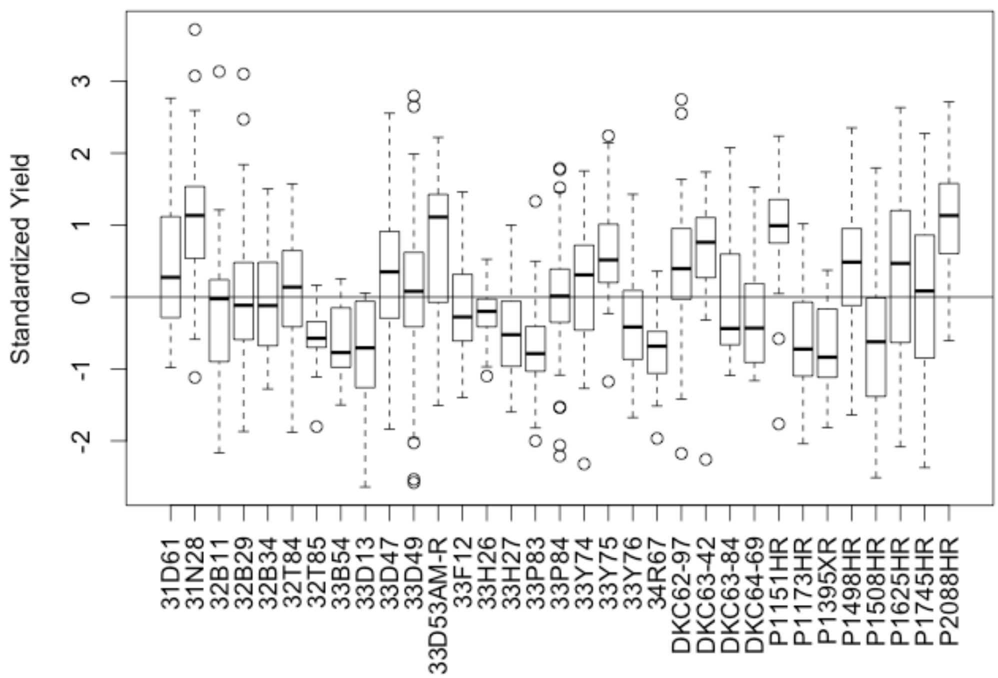

Figure 3.13—Irrigated yields (standardized) by common cultivar. Boxes represent one standard deviation around the mean; whiskers represent full range of data. Line represents mean yield.

There were no significant interactions between cultivar and early-growth TT34 (Chisq(32)=43.8, p=0.08), or grain-fill radiation (Chisq(32)=42.6 , p=0.11).

The early-growth TT34 by grain-fill TT34 interaction remained significant, and the fact that it did not interact significantly with cultivar may suggest that the cultivars tested all demonstrated the same tendency towards thermo-acclimation.

There was significant variation in individual cultivar response to sensitive period TT34 (Chisq(32)=70.9, p=9.1 e-05), grain-fill TT34 (Chisq(32)=51, p=0.02), early-growth radiation (Chisq(32)=65.7, p=4.1e-04), and sensitive-period radiation (Chisq(32)=62.2, p=1.1e-03). Figure 3.14 shows the magnitude of temperature – stress response modification in cultivars that had yield responses to high temperatures that were significantly different than the overall population.

The model which includes cultivar interactions with climate (degrees of freedom = 177, AIC=2914) was not significantly better than a model which accounted for yield response to cultivar as a random effect (degrees of freedom = 18, AIC = 2892), suggesting that looking at specific cultivar interactions with climate does not significantly improve our understanding of overall population yield trends, given the degrees of freedom it costs the model, and model may be overfit. Even when "cultivar" as a factor showed a significant interaction with a climate variable, looking at the model summary indicates that, in reality, only several cultivars out of those sampled would have a significantly modified yield response to this variable.

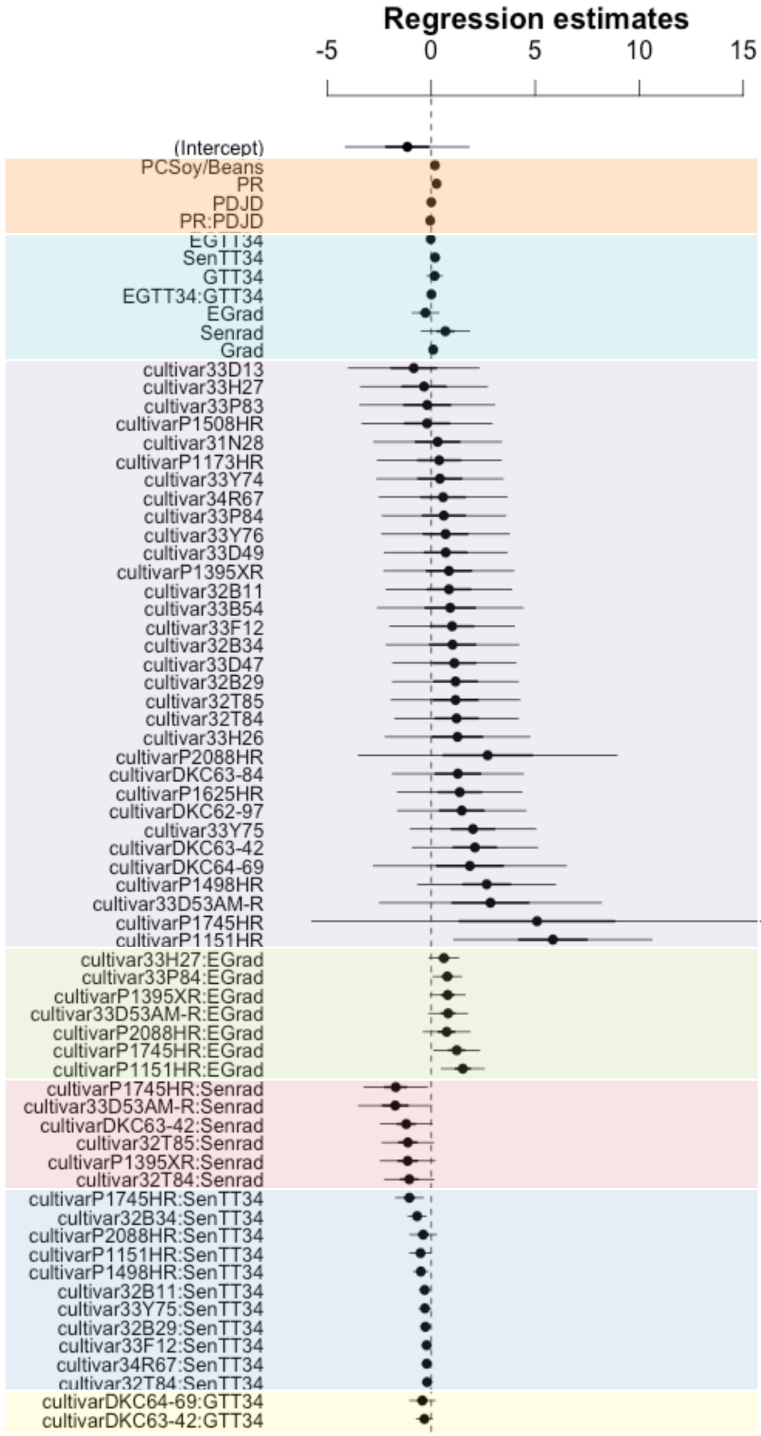

Figure 3.14: Coefficient plot for model showing significant cultivar by climate interactions. Effects highlighted in orange are management, teal are climate, purple are cultivar, green are cultivar effect modification by early-growth radiation, pink are cultivar effect modification by radiation during silking, blue are cultivar effect modification by TT34 during silking, and yellow are cultivar effect modification by TT34 during grain-fill.

The regression coefficient plot (Figure 3.14) only shows cultivars that demonstrated climate susceptibilities or resiliencies that were significantly different from the climate responses of all cultivars used. “Regression estimates” describe the yield response (standard deviations of yield, or 1.76 MT/ha) per standard-deviation change in predictor variable. Error bars represent one and two standard deviations from the estimate. Climate variables are denoted as described in Section 2.4.3. Interaction terms between specific cultivars and climate variables show the amount that a given climate variable would be modified by a one unit change in predictor variable (standardized radiation, log-transformed TT34), and are denoted by a colon between the cultivar’s name and a second variable. As an example, cultivar P1745HR has an above-average yield response, the plotted coefficient for cultivarP1745HR:EGrad tells us the amount that the yield response for P1745HR is increased for each unit increase in EGrad (early-growth radiation).

The character of this temperature sensitivity is shown in Figure 3.15: a lsmip (Rusell, 2014) demonstrating performance variability of cultivars sensitive to high temperatures around silking. Projected yield response of sensitive cultivars (Pioneer 32B34, Pioneer P1498HR, and Pioneer P2088HR), and cultivars which showed no significant interaction with high temperatures during silking (Pioneer 33D13, Pioneer 1395XR, and Pioneer 33Y75), are shown under increasing levels of log-transformed sensitive-period TT34. We see several cultivars show statistically significant but low magnitude negative response to TT34 during the sensitive period or during grain-fill, though this response does not necessary lead to net yield losses.

Instead we see that performance variability of "sensitive" cultivars is highest under no heat stress, and that the main impact of high temperatures during silking is to level out the performance levels of different cultivars.

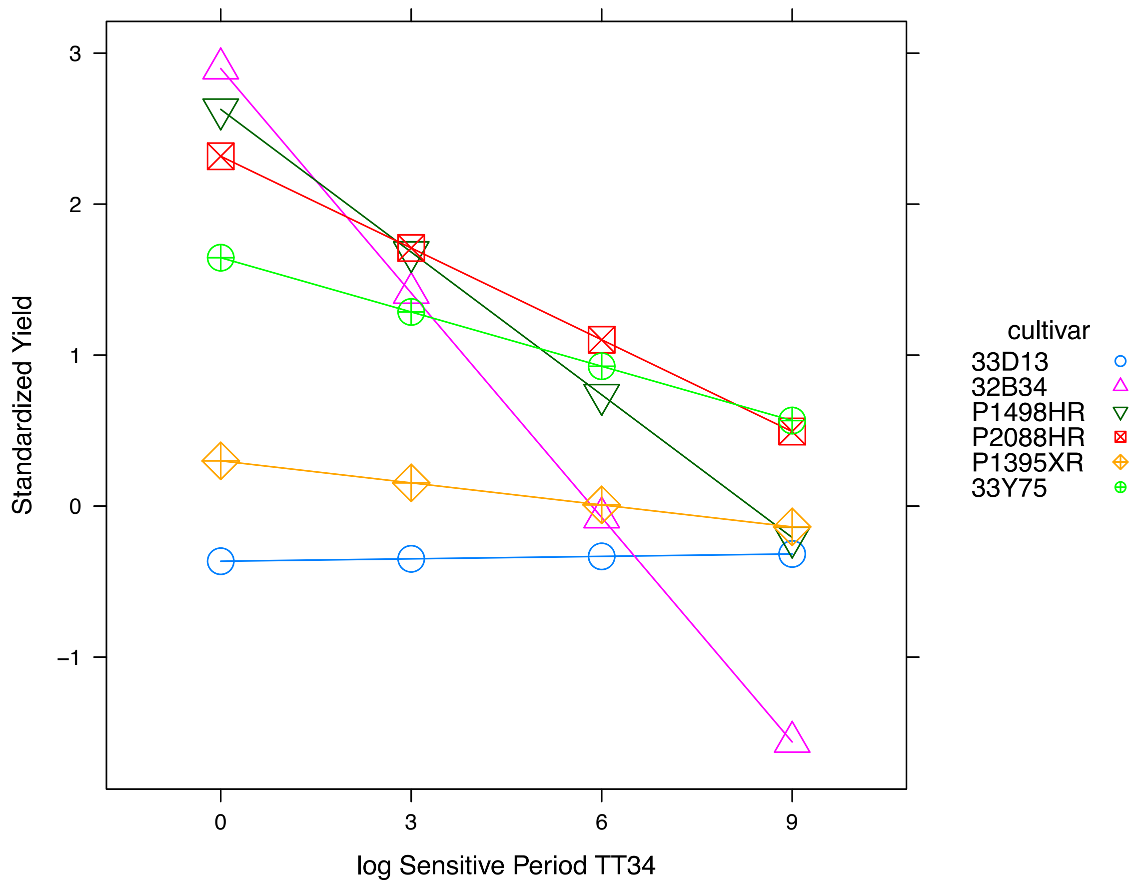

Figure 3.15: Variability in cultivar performance (standardized yield) with increasing levels of TT34 around silking.

We also noted an interesting, though somewhat more enigmatic, trend in six cultivars towards decreasing yields with increasing radiation during the sensitive period. Once again, because we modeled the periods of our growth development phases using thermal time, there's a chance that this response is an indirect artifact of beneficial temperature impacts.

Earlier results suggest that elite cultivars, as a population, are not uniquely susceptible to high temperatures coinciding with silking, even though this is the period where most temperature-sensitive physiological processes linked to yield formation occur. Seeing that certain cultivars are susceptible to high temperatures around silking may suggest that observed lack of sensitivity to heat stress during the "sensitive period" in the overall population may in fact be an artifact of targeting breeding practices to improved stress tolerance around silking. In other words, the fact that certain cultivars are susceptible to heat stress during silking, even though this interaction is not significant in the population as a whole, suggests that temperature stress tolerance is mediated by genetics. Furthermore, it suggests that the majority of modern cultivars have this genetic stress tolerance.

4 CONCLUSION

4.1 HEAT STRESS IN IRRIGATED MAIZE

The yield response to heat stress appears to be minimal in irrigated maize, even when the crop is exposed to anomalously high temperatures, such as were seen in the US Corn Belt in 2012. In contrast to recent statistical/econometric studies that did not adjust for soil moisture stress, we saw no significant yield response to high daytime air temperatures or vapor pressure deficits when these variables are calculated over the entire growing season. When looked at by growth development phase, we see evidence that high temperatures are impacting yield gains from radiation during grain-fill, but we also see that this negative impact is positively modified if the crop experienced above-optimum temperatures early in its growth. This trend is supported by evidence of acquired thermo-tolerance in the literature, and suggests that consistently high temperatures may in fact lead to a positive yield response in maize. Evidence of acquired thermo-tolerance takes on particular significance in the context of projecting yield response to climate change, when the goal is to consider crop response to a shifted temperature regime.

Radiation appears to be the most directly yield-limiting climate variable in irrigated maize systems, with increased growing season radiation associated with agronomically significant yield gains. Yield response to radiation appears strongest during grain-fill and early-growth, with no significant relationship between yields and sensitive-period radiation observed. Since the duration of our growing season was modeled using thermal time, any yield impact from increased rates of phenologic development would have been captured with this radiation variable. In turn, to capitalize on yield gain from increased radiation with increasing air temperatures, longer maturity-class cultivars can be selected. Night temperatures also have a significant, inverse relationship to maize yields, though no evidence of night time heat stress mechanism separate from increased rates of phenologic development (as was captured with the radiation variable), or impacts from decreased radiation associated with higher night temperatures, could be determined from this data set.

Planting dates and cultivar maturity class significantly modifies crop yield response to high temperatures. Slightly delaying planting is also associated with reduction in negative temperature impacts during grain-fill, which may relate to mechanisms for acquired thermo-tolerance in maize, as delayed planting would be associated with increased temperatures during early vegetative growth. Longer season cultivars are associated with decreased sensitivity to high temperatures in early-growth and grain-fill. One possible reason for this is that high levels of above-optimum temperatures may be contributing to increased development rates. Longer season cultivars spend more time growing and intercepting radiation per unit thermal time than shorter season cultivars. Another reason may be that longer season cultivars are locally adapted to higher temperatures, and may therefore be genetically predisposed to increased heat stress tolerance.

Looking at individual cultivar response to climate variables provides further evidence that genetic mechanisms, besides cultivar maturity class, influence heat stress response in maize. Several cultivars show unique sensitivity to heat stress, including heat stress that occurred during the period around silking. High temperatures around silking are not significantly related to yields for the population as a whole, and including an interaction for these few cultivars did not represent a significant improvement over a model without a term for sensitive period silking. Yield response to management is orders of magnitude greater than the yield response to significant climate variables, suggesting that optimizing from within the range of current cultural practices in the U.S. Corn Belt is more than sufficient to offset any yield declines projected from extreme high temperatures experienced over the geographic and temporal scope of the study.

4.2 IMPLICATIONS FOR YIELD PROJECTIONS IN A CHANGING CLIMATE

Collinearity in climate data generates model outputs that are extremely hard to interpret. Returning to the principal component analysis biplot of our climate data (Figure 3.2), we see evidence of why capturing temperature impacts, and predicting yields by extrapolating from these temperature impacts, may be so problematic. PC1, which explained 73% of variability in our climate data, was an analogue to temperature-like climate variables. This tells us that air temperature is a strongly correlated with many diverse climate variables, which may themselves have discrete relationships with a crop. Therefore, in statistical analysis, temperature can be simultaneously picking up multiple overlapping climate-crop interactions.

But the fact that air temperature may serve as an indicator for many overlapping crop-climate impacts does not in any way mean that increasing temperature will lead to additive crop-climate impacts on yields. The unique correlation structure between climate variables can be considered one of the defining characteristics of a climate system (Fovell and Fovell, 1993). Altering a single climate variable within a climate system (such as temperature) would be expected to lead to a change in the correlation structure between temperature and other climate variables. If a regression model identified a yield response to climate that was well represented by temperature, given the correlation structure between temperature and the other climate variables in the dataset used for model fitting, the coefficient of yield response would in fact be representing the net impact of multiple complex crop-climate interaction mechanisms that were masked by this climate system-specific correlation structure. In other words, the yield-temperature coefficient might simultaneously be capturing benefits from increased radiation and losses from water stress, for example. If temperatures shifted, the correlation between temperature, radiation, and moisture would shift. The coefficient of correlation between yields and temperature, given that temperature no longer delineates the same relationship between other yield-limiting climate variables in the climate system, would no longer be valid.

Contextualizing this analysis in the larger debate about whether statistical/econometric models can achieve the resolution necessary to make accurate yield projections under climate change scenarios, we found that statistical modeling can be a very useful tool in the discovery of potential large-scale trends in climate-crop interactions, but conclude that these impacts should be quantified in more controlled environments, where individual climate variables can be modified to determine net impacts. Controlling for moisture impacts (through use of irrigated maize contest entries) was critical to our analysis. Even with our large data set (nearly 2000 yield records), overfitting in models attempting to capture complex management-climate interactions was problematic.

This analysis does suggest that acclimation to heat stress, or acquired thermo-tolerance, in maize cropping systems may be an important consideration for predicting yield response to shifted temperature regimes. It also suggests that mechanism for direct temperature stress impacts in maize, after controlling for soil moisture stress through irrigation and impacts of increased development rates commonly captured in maize process-based models, appear to be strongest during grain-fill, and may have to do with temperature impacts on radiation use efficiency during grain-fill. We also see evidence of adaptation mechanisms, both in maize cropping systems and in maize genetics, to observed temperature impacts that are associated with yield response of sufficient magnitude to offset any climate-related yield losses observed in our dataset.

This research also suggests that carefully parameterized crop process models, not statistical models, are necessary to make mechanistic and accurate predictions of yield response to shifted climate variables. Due to spatially and temporally explicit correlation structures in climate data from observational datasets, accurate quantifications of these yield response mechanisms (acquired thermo-tolerance, yield impacts of high temperatures during grain-fill) would be best done experimentally under controlled conditions.

APPENDIX A: BASE MODEL SUMMARY

Appendix A: BASE MODEL

Linear mixed model fit by maximum likelihood ['merModLmerTest']

Formula: yield ~ Planting rate + Planting date + Planting rate: Planting date + Cultivar GDD to mat + Previous crop + (1|location) + (1|location:farmID) + (1 | cultivar) + (1 | year)

AIC	BIC	logLik	deviance	df.resid
4419	4485.8	-2197.5	4395	1917

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.2366	-0.5239	0.0227	0.5425	2.9781

Random Effects:

Groups	Name	Variance	Std.Dev.
location:farmID	(Intercept)	0.22824	0.4777
cultivar	(Intercept)	0.0608	0.2466
location	(Intercept)	0.04826	0.2197
inter-annual	(Intercept)	0.11972	0.346
Residual		0.35616	0.5968

Number of obs: 1929, groups: csv:farmID, 990; cultivar, 312; csv, 66; year, 8

Fixed Effects:

	Estimate	Std. Error	df	t value	Pr(>|t|)	
(Intercept)	-0.36522	0.1338	10.8	-2.73	0.01983	*
planting rate	0.28756	0.02164	1589.4	13.286	<2.00E-16	***
planting date	-0.03688	0.02443	1624.1	-1.509	0.131391	
Cultivar GDD to maturity	0.08004	0.02642	328	3.029	0.002648	**
Prev. Crop: Other	0.14709	0.0805	1852.8	1.827	0.067822	.
Prev. Crop: Soy/Beans	0.13209	0.04038	1920.9	3.271	0.001091	**
Planting rate: planting date	-0.05434	0.01601	1707.6	-3.394	0.000704	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

APPENDIX B: RADIATION BY TT34 MODEL SUMMARY

Appendix B: Radiation by TT34 model

Linear mixed model fit by maximum likelihood ['merModLmerTest']

Formula: yield ~ Planting rate + Planting date + Planting rate: Planting date + Cultivar GDD to mat + Previous crop + EGTT34 + GTT34 + EGTT34:GTT34+ Egrad + Grad + Grad: GTT34 + (1|location) + (1|location:farmID) + (1 | cultivar) + (1 | year)

Data: std

AIC	BIC	logLik	deviance	df.resid
4381.5	4481.7	-2172.8	4345.5	1911

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.13408	-0.53224	0.02155	0.52396	2.8972

Random Effects:

Groups	Name	Variance	Std.Dev.
location:farmID	(Intercept)	0.22813	0.4776
cultivar	(Intercept)	0.05492	0.2343
location	(Intercept)	0.03364	0.1834
inter-annual	(Intercept)	0.10226	0.3198
Residual		0.34822	0.5901

Number of obs: 1929, groups: csv:farmID, 990; cultivar, 312; csv, 66; year, 8

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(>|t|)	
(Intercept)	-3.93E-01	1.43E-01	1.80E+01	-2.759	0.012906	*
planting rate	2.97E-01	2.15E-02	1.58E+03	13.817	<2.00E-16	***
planting date	-2.01E-02	2.88E-02	1.12E+03	-0.698	0.485525	
Cultivar GDD to maturity	6.42E-02	2.75E-02	3.96E+02	2.334	0.020116	*
Prev. Crop: Other	1.28E-01	7.95E-02	1.85E+03	1.61	0.107601	
Prev. Crop: Soy/Beans	1.40E-01	4.00E-02	1.92E+03	3.493	0.000489	***
EGrad	1.11E-01	3.15E-02	6.26E+02	3.515	0.000472	***
Grad	1.66E-01	5.04E-02	1.45E+03	3.283	0.001051	**
EGTT34	-1.94E-02	1.56E-02	1.74E+03	-1.246	0.212999	
GTT34	-1.53E-02	1.16E-02	1.34E+03	-1.323	0.186088	
Planting rate: planting date	-5.67E-02	1.58E-02	1.72E+03	-3.593	0.000336	***
EGTT34:GTT34	7.51E-03	2.21E-03	1.58E+03	3.399	0.000692	***
Grad:GTT34	-1.81E-02	6.59E-03	1.72E+03	-2.751	0.006004	**

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

APPENDIX C: MANAGEMENT BY CLIMATE MODEL SUMMARY

Note: this model is considered improved relative to the Radition by TT34 model, based on the AIC; but is considered overfit, relative to Radiation by TT34 model (Appendix B), based on increase in BIC.

APPENDIX C: MANAGEMENT BY CLIMATE

Linear mixed model fit by maximum likelihood ['merModLmerTest']

Formula: yield ~ Planting rate + Planting date + Planting rate: Planting date + Cultivar GDD to mat + Previous crop +
EGrad + Grad + EGTT34:GTT34 + Grad:GTT34 + PDJD:GTT34 +
PDJD:Grad:GTT34 +CultGDD:EGTT34 + CultGDD:GTT34 +
CultGDD:EGTT34:GTT34 + CultGDD:Grad:GTT34 +
(1 | location) + (1 | location:farmID) + (1 | cultivar) + (1 | year)

AIC	BIC	logLik	deviance	df.resid
4370.2	4503.7	-2161.1	4322.2	1905

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.1951	-0.5242	0.0249	0.5375	2.851

Random Effects:

Groups	Name	Variance	Std.Dev.
location:farmID	(Intercept)	0.22518	0.4745
cultivar	(Intercept)	0.05044	0.2246
location	(Intercept)	0.03401	0.1844
inter-annual	(Intercept)	0.1021	0.3195
Residual		0.34533	0.5876

Number of obs: 1929, groups: csv:farmID, 990; cultivar, 312; csv, 66; year, 8

Fixed Effects:

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-3.85E-01	1.42E-01	1.81E+01	-2.701	0.014559
Planting rate	3.01E-01	2.14E-02	1.56E+03	14.033	<2E-16
Planting date	-2.05E-01	6.25E-02	1.72E+03	-3.286	0.001038
Previous Crop:Other	1.11E-01	7.93E-02	1.86E+03	1.393	0.163777
Previous Crop: Soy/Beans	1.37E-01	3.98E-02	1.92E+03	3.443	0.000587
Cultivar GDD to maturity	-1.41E-02	5.98E-02	1.10E+03	-0.236	0.813351
Early-growth TT34	-4.77E-03	1.62E-02	1.72E+03	-0.295	0.767799
Grain-fill TT34	-1.85E-02	1.16E-02	1.37E+03	-1.599	0.110049
Early-growth radiation	1.08E-01	3.19E-02	6.01E+02	3.384	0.000762
Grain-fill radiation	1.83E-01	5.38E-02	1.47E+03	3.406	0.000676
Planting rate by planting date	-6.31E-02	1.59E-02	1.73E+03	-3.965	7.63E-05
Early-growth by grain-fill TT34	5.50E-03	2.33E-03	1.53E+03	2.355	0.018662
Grain-fill radiation by TT34	-2.30E-02	7.16E-03	1.70E+03	-3.217	0.001322
Planting date by grain-fill TT34	2.95E-02	8.09E-03	1.83E+03	3.646	0.000274
Cultivar GDD to maturity by early-growth TT34	1.48E-02	1.40E-02	1.76E+03	1.054	0.291986
Cultivar GDD to maturity by grain-fill TT34	2.51E-02	9.65E-03	1.56E+03	2.6	0.009398
Planting date by grainfill radiation by TT34	5.57E-03	2.96E-03	1.78E+03	1.883	0.059929
Cultivar GDD to mat. by EGTT34:GTT34	-4.01E-03	2.05E-03	1.77E+03	-1.953	0.050978
Cultivar GDD to mat. by G radiation by TT34	5.07E-03	2.74E-03	1.19E+03	1.846	0.065165

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

APPENDIX D: CULTIVAR BY CLIMATE MODEL SUMMARY

Note: this model is fit to a different dataset than models summarized in appendices A-C, so AIC and BIC cannot be compared between these models. This model has a higher AIC and BIC than a model which includes cultivar as a random effect, suggesting that this model is overfit.

Linear mixed model fit by maximum likelihood ['merModLmerTest']

Formula: yield ~ Planting rate + Planting date + Planting rate: Planting date + Previous crop + cultivar +
EGrad + Senrad + Grad + EGrad:cultivar +Senrad:cultivar+
EGTT34 + SenTT34 + GTT34 + EGTT34:GTT34+
SenTT34:cultivar + GTT34:cultivar +
(1|location) + (1|location:farmID) + (1 | year)

AIC	BIC	logLik	deviance	df.resid
2903.3	3815.8	-1274.6	2549.3	1104

Scaled	residuals			
Min	1Q	Median	3Q	Max
-3.2369	-0.5549	0.003	0.5803	3.5026

Random Effects:

Groups	Name	Variance	Std.Dev.
csv:farmID	(Intercept)	0.19976	0.4469
csv	(Intercept)	0.02215	0.1488
yearfac	(Intercept)	0.16086	0.4011
Residual		0.26435	0.5141

Number of obs: 1281, groups: location:farmID, 733; location, 65; year, 8

Fixed Effects:

	Estimate	Std. Error	df	t value	Pr(>|t|)	
(Intercept)	-1.15E+00	1.52E+00	1.12E+03	-0.758	0.44889	
planting rate	2.58E-01	2.53E-02	1.08E+03	10.194	<2.00E-16	***
planting date	1.54E-03	3.89E-02	8.99E+02	0.04	0.96832	
Prev. Crop: Other	3.48E-02	1.07E-01	1.26E+03	0.324	0.7458	
Prev. Crop: Soy/Beans	1.81E-01	4.61E-02	1.26E+03	3.929	9.01E-05	***
cultivar31N28	3.11E-01	1.57E+00	1.21E+03	0.199	0.84266	
cultivar32B11	8.54E-01	1.54E+00	1.15E+03	0.556	0.57847	
cultivar32B29	1.17E+00	1.54E+00	1.17E+03	0.759	0.44802	
cultivar32B34	1.03E+00	1.63E+00	1.17E+03	0.632	0.52779	
cultivar32T84	1.22E+00	1.51E+00	1.14E+03	0.804	0.42167	
cultivar32T85	1.17E+00	1.58E+00	1.17E+03	0.739	0.45994	
cultivar33B54	9.13E-01	1.78E+00	1.22E+03	0.512	0.60881	

cultivar33D13	-8.40E-01	1.61E+00	1.15E+03	-0.523	0.60088	
cultivar33D47	1.11E+00	1.51E+00	1.14E+03	0.737	0.46129	
cultivar33D49	6.99E-01	1.51E+00	1.14E+03	0.464	0.64255	
cultivar33D53AM-R	2.85E+00	2.72E+00	1.03E+03	1.047	0.29531	
cultivar33F12	1.01E+00	1.53E+00	1.15E+03	0.66	0.50968	
cultivar33H26	1.27E+00	1.78E+00	1.20E+03	0.712	0.47637	
cultivar33H27	-3.47E-01	1.56E+00	1.16E+03	-0.223	0.82343	
cultivar33P83	-1.90E-01	1.65E+00	1.19E+03	-0.115	0.90841	
cultivar33P84	6.05E-01	1.51E+00	1.13E+03	0.4	0.68957	
cultivar33Y74	4.17E-01	1.55E+00	1.16E+03	0.269	0.78776	
cultivar33Y75	2.01E+00	1.54E+00	1.15E+03	1.306	0.19167	
cultivar33Y76	6.91E-01	1.57E+00	1.16E+03	0.441	0.65933	
cultivar34R67	5.72E-01	1.57E+00	1.13E+03	0.365	0.71548	
cultivarDKC62-97	1.47E+00	1.57E+00	1.16E+03	0.936	0.34972	
cultivarDKC63-42	2.10E+00	1.53E+00	1.16E+03	1.37	0.17086	
cultivarDKC63-84	1.28E+00	1.61E+00	1.16E+03	0.798	0.42517	
cultivarDKC64-69	1.86E+00	2.37E+00	1.15E+03	0.785	0.43242	
cultivarP1151HR	5.85E+00	2.43E+00	1.16E+03	2.408	0.01618	*
cultivarP1173HR	3.83E-01	1.52E+00	1.14E+03	0.252	0.80097	
cultivarP1395XR	8.51E-01	1.59E+00	1.16E+03	0.535	0.59299	
cultivarP1498HR	2.67E+00	1.69E+00	1.18E+03	1.578	0.11477	
cultivarP1508HR	-1.99E-01	1.59E+00	1.18E+03	-0.125	0.9006	
cultivarP1625HR	1.37E+00	1.53E+00	1.14E+03	0.899	0.36873	
cultivarP1745HR	5.09E+00	5.52E+00	1.05E+03	0.921	0.35722	
cultivarP2088HR	2.72E+00	3.17E+00	1.19E+03	0.856	0.39243	
EGrad	-2.75E-01	3.25E-01	1.27E+03	-0.845	0.3984	
Senrad	6.79E-01	5.94E-01	7.84E+02	1.142	0.25376	
Grad	9.47E-02	4.45E-02	1.07E+03	2.126	0.03373	*
EGTT34	-2.45E-02	2.07E-02	9.84E+02	-1.185	0.23647	
SenTT34	1.83E-01	1.09E-01	1.05E+03	1.685	0.0923	.
GTT34	1.61E-01	1.85E-01	1.23E+03	0.871	0.38415	
planting rate: planting date	-4.84E-02	1.96E-02	1.06E+03	-2.472	0.01359	*
EGTT34:GTT34	7.61E-03	2.93E-03	9.70E+02	2.603	0.00938	**
cultivar31N28:SenTT34	-1.30E-01	1.17E-01	1.07E+03	-1.112	0.26648	
cultivar32B11:SenTT34	-3.15E-01	1.27E-01	1.05E+03	-2.476	0.01346	*
cultivar32B29:SenTT34	-2.80E-01	1.16E-01	1.11E+03	-2.408	0.0162	*
cultivar32B34:SenTT34	-6.79E-01	2.20E-01	1.15E+03	-3.079	0.00212	**
cultivar32T84:SenTT34	-1.96E-01	1.14E-01	1.06E+03	-1.718	0.08604	.
cultivar32T85:SenTT34	-1.95E-01	1.33E-01	1.16E+03	-1.467	0.14256	
cultivar33B54:SenTT34	-1.47E-01	1.30E-01	1.09E+03	-1.128	0.25964	
cultivar33D13:SenTT34	-1.78E-01	1.30E-01	1.26E+03	-1.369	0.17114	
cultivar33D47:SenTT34	-1.43E-01	1.11E-01	1.06E+03	-1.29	0.19719	
cultivar33D49:SenTT34	-9.42E-02	1.11E-01	1.06E+03	-0.846	0.39747	

cultivar33D53AM-R:SenTT34	-7.24E-02	5.92E-01	1.05E+03	-0.122	0.90282	
cultivar33F12:SenTT34	-2.21E-01	1.16E-01	1.06E+03	-1.905	0.05708	.
cultivar33H26:SenTT34	-2.02E-01	1.99E-01	1.26E+03	-1.013	0.31129	
cultivar33H27:SenTT34	-1.44E-01	1.17E-01	1.03E+03	-1.227	0.22021	
cultivar33P83:SenTT34	-9.85E-02	1.56E-01	9.54E+02	-0.633	0.52705	
cultivar33P84:SenTT34	-1.53E-01	1.17E-01	1.05E+03	-1.311	0.18997	
cultivar33Y74:SenTT34	-9.35E-02	1.15E-01	1.06E+03	-0.816	0.41461	
cultivar33Y75:SenTT34	-3.03E-01	1.43E-01	1.10E+03	-2.114	0.03476	*
cultivar33Y76:SenTT34	-1.85E-01	1.24E-01	1.00E+03	-1.485	0.13788	
cultivar34R67:SenTT34	-2.16E-01	1.18E-01	1.11E+03	-1.824	0.06845	.
cultivarDKC62-97:SenTT34	-1.38E-01	1.34E-01	1.10E+03	-1.03	0.30344	
cultivarDKC63-42:SenTT34	-2.00E-01	1.21E-01	1.16E+03	-1.657	0.09788	.
cultivarDKC63-84:SenTT34	-2.20E-01	1.64E-01	1.08E+03	-1.343	0.17966	
cultivarDKC64-69:SenTT34	-9.44E-02	2.28E-01	1.23E+03	-0.415	0.67829	
cultivarP1151HR:SenTT34	-5.17E-01	2.64E-01	1.20E+03	-1.956	0.05071	.
cultivarP1173HR:SenTT34	-1.24E-01	1.23E-01	1.03E+03	-1.005	0.31506	
cultivarP1395XR:SenTT34	-2.32E-01	1.43E-01	1.24E+03	-1.623	0.10475	
cultivarP1498HR:SenTT34	-4.98E-01	1.75E-01	1.02E+03	-2.853	0.00443	**
cultivarP1508HR:SenTT34	-3.74E-03	1.41E-01	8.98E+02	-0.026	0.97891	
cultivarP1625HR:SenTT34	-1.85E-01	1.16E-01	1.03E+03	-1.589	0.11247	
cultivarP1745HR:SenTT34	-1.05E+00	3.35E-01	1.16E+03	-3.128	0.0018	**
cultivarP2088HR:SenTT34	-3.86E-01	3.23E-01	1.21E+03	-1.194	0.23278	
cultivar31N28:GTT34	7.76E-03	1.93E-01	1.22E+03	0.04	0.9679	
cultivar32B11:GTT34	-8.50E-02	1.94E-01	1.24E+03	-0.437	0.66197	
cultivar32B29:GTT34	-1.00E-01	1.91E-01	1.23E+03	-0.525	0.59992	
cultivar32B34:GTT34	2.62E-01	2.52E-01	1.20E+03	1.039	0.29914	
cultivar32T84:GTT34	-1.85E-01	1.87E-01	1.24E+03	-0.988	0.32313	
cultivar32T85:GTT34	-2.45E-01	2.02E-01	1.25E+03	-1.214	0.22496	
cultivar33B54:GTT34	-2.53E-01	2.47E-01	1.24E+03	-1.023	0.30666	
cultivar33D13:GTT34	1.56E-02	1.97E-01	1.24E+03	0.079	0.93666	
cultivar33D47:GTT34	-1.77E-01	1.86E-01	1.23E+03	-0.954	0.34047	
cultivar33D49:GTT34	-2.10E-01	1.85E-01	1.23E+03	-1.133	0.25725	
cultivar33D53AM-R:GTT34	-5.21E-01	6.20E-01	9.49E+02	-0.84	0.40128	
cultivar33F12:GTT34	-1.67E-01	1.89E-01	1.24E+03	-0.884	0.37705	
cultivar33H26:GTT34	-2.10E-01	2.15E-01	1.26E+03	-0.977	0.329	
cultivar33H27:GTT34	-6.87E-02	1.96E-01	1.25E+03	-0.351	0.72543	
cultivar33P83:GTT34	-1.76E-01	2.13E-01	1.25E+03	-0.827	0.40822	
cultivar33P84:GTT34	-1.67E-01	1.88E-01	1.24E+03	-0.892	0.3724	
cultivar33Y74:GTT34	-1.38E-01	1.91E-01	1.24E+03	-0.722	0.47041	
cultivar33Y75:GTT34	-1.12E-01	1.95E-01	1.25E+03	-0.573	0.56655	
cultivar33Y76:GTT34	-1.43E-01	1.97E-01	1.25E+03	-0.726	0.46774	
cultivar34R67:GTT34	-1.67E-01	1.99E-01	1.23E+03	-0.839	0.4017	

cultivarDKC62-97:GTT34	-2.91E-01	1.99E-01	1.24E+03	-1.462	0.14393	
cultivarDKC63-42:GTT34	-3.28E-01	1.93E-01	1.25E+03	-1.699	0.08948	.
cultivarDKC63-84:GTT34	-2.47E-01	2.14E-01	1.25E+03	-1.155	0.24845	
cultivarDKC64-69:GTT34	-4.26E-01	3.09E-01	1.19E+03	-1.376	0.16897	
cultivarP1151HR:GTT34	-3.91E-01	3.92E-01	1.24E+03	-0.998	0.31853	
cultivarP1173HR:GTT34	-1.41E-01	1.88E-01	1.24E+03	-0.75	0.45338	
cultivarP1395XR:GTT34	-1.59E-01	2.05E-01	1.25E+03	-0.776	0.43811	
cultivarP1498HR:GTT34	-6.60E-02	2.17E-01	1.24E+03	-0.304	0.76089	
cultivarP1508HR:GTT34	-2.06E-01	2.05E-01	1.24E+03	-1.006	0.3144	
cultivarP1625HR:GTT34	-1.91E-01	1.88E-01	1.24E+03	-1.016	0.30996	
cultivarP1745HR:GTT34	1.63E-01	6.57E-01	1.06E+03	0.249	0.80373	
cultivarP2088HR:GTT34	-1.34E-01	4.10E-01	1.27E+03	-0.326	0.7446	
cultivar31N28:EGrad	3.91E-01	3.80E-01	1.12E+03	1.029	0.30385	
cultivar32B11:EGrad	8.44E-02	4.25E-01	1.23E+03	0.198	0.84282	
cultivar32B29:EGrad	1.72E-01	3.73E-01	1.24E+03	0.461	0.64486	
cultivar32B34:EGrad	2.43E-01	3.72E-01	1.27E+03	0.653	0.51412	
cultivar32T84:EGrad	3.94E-01	3.46E-01	1.26E+03	1.141	0.25411	
cultivar32T85:EGrad	8.60E-01	3.97E-01	1.27E+03	2.164	0.03063	*
cultivar33B54:EGrad	1.52E-01	4.13E-01	1.24E+03	0.367	0.71333	
cultivar33D13:EGrad	6.48E-01	4.39E-01	1.26E+03	1.476	0.14031	
cultivar33D47:EGrad	1.55E-01	3.32E-01	1.26E+03	0.465	0.64213	
cultivar33D49:EGrad	4.95E-01	3.25E-01	1.26E+03	1.523	0.12789	
cultivar33D53AM-R:EGrad	8.12E-01	4.76E-01	1.10E+03	1.706	0.08833	.
cultivar33F12:EGrad	3.32E-01	3.65E-01	1.27E+03	0.908	0.36417	
cultivar33H26:EGrad	1.28E-01	5.64E-01	1.26E+03	0.228	0.82005	
cultivar33H27:EGrad	6.08E-01	3.61E-01	1.24E+03	1.684	0.09234	.
cultivar33P83:EGrad	1.06E+00	7.05E-01	9.28E+02	1.506	0.13228	
cultivar33P84:EGrad	7.71E-01	3.50E-01	1.26E+03	2.205	0.02765	*
cultivar33Y74:EGrad	5.59E-01	3.59E-01	1.22E+03	1.557	0.11971	
cultivar33Y75:EGrad	-3.21E-02	4.20E-01	1.27E+03	-0.076	0.93918	
cultivar33Y76:EGrad	1.47E-01	4.61E-01	1.17E+03	0.318	0.75076	
cultivar34R67:EGrad	3.40E-01	3.88E-01	1.26E+03	0.877	0.38051	
cultivarDKC62-97:EGrad	4.11E-01	3.68E-01	1.27E+03	1.114	0.26542	
cultivarDKC63-42:EGrad	5.83E-01	3.86E-01	1.27E+03	1.51	0.13139	
cultivarDKC63-84:EGrad	-4.75E-01	4.90E-01	1.25E+03	-0.969	0.33256	
cultivarDKC64-69:EGrad	-2.65E-01	4.04E-01	1.27E+03	-0.656	0.51205	
cultivarP1151HR:EGrad	1.52E+00	5.25E-01	1.22E+03	2.895	0.00386	**
cultivarP1173HR:EGrad	5.07E-01	3.59E-01	1.23E+03	1.413	0.15793	
cultivarP1395XR:EGrad	7.93E-01	4.26E-01	1.25E+03	1.863	0.06265	.
cultivarP1498HR:EGrad	4.20E-01	3.48E-01	1.25E+03	1.206	0.2282	
cultivarP1508HR:EGrad	-3.88E-01	5.67E-01	1.03E+03	-0.684	0.4941	
cultivarP1625HR:EGrad	3.99E-01	3.31E-01	1.26E+03	1.205	0.22826	
cultivarP1745HR:EGrad	1.23E+00	5.61E-01	1.23E+03	2.188	0.02889	*

cultivarP2088HR:EGrad	7.43E-01	5.72E-01	1.15E+03	1.3	0.19398	
cultivar31N28:Senrad	-7.15E-01	6.12E-01	9.86E+02	-1.168	0.24318	
cultivar32B11:Senrad	-6.76E-01	6.21E-01	8.68E+02	-1.089	0.2764	
cultivar32B29:Senrad	-4.07E-01	6.28E-01	9.00E+02	-0.649	0.51648	
cultivar32B34:Senrad	-9.73E-01	6.29E-01	8.39E+02	-1.548	0.12209	
cultivar32T84:Senrad	-1.05E+00	6.04E-01	8.25E+02	-1.746	0.0812	.
cultivar32T85:Senrad	-1.12E+00	6.28E-01	8.62E+02	-1.791	0.07362	.
cultivar33B54:Senrad	-7.06E-01	6.59E-01	9.71E+02	-1.073	0.28368	
cultivar33D13:Senrad	-4.36E-01	6.73E-01	9.79E+02	-0.648	0.51698	
cultivar33D47:Senrad	-6.18E-01	6.00E-01	8.04E+02	-1.03	0.30342	
cultivar33D49:Senrad	-6.85E-01	5.95E-01	7.98E+02	-1.15	0.2503	
cultivar33D53AM-R:Senrad	-1.73E+00	8.97E-01	1.25E+03	-1.928	0.05404	.
cultivar33F12:Senrad	-9.86E-01	6.12E-01	8.39E+02	-1.612	0.10729	
cultivar33H26:Senrad	-6.56E-01	6.46E-01	8.68E+02	-1.016	0.30988	
cultivar33H27:Senrad	-5.86E-01	6.23E-01	8.68E+02	-0.94	0.34737	
cultivar33P83:Senrad	-6.26E-01	6.37E-01	8.82E+02	-0.982	0.32646	
cultivar33P84:Senrad	-6.30E-01	6.07E-01	8.22E+02	-1.037	0.30011	
cultivar33Y74:Senrad	-7.31E-01	5.98E-01	7.90E+02	-1.222	0.22197	
cultivar33Y75:Senrad	-5.89E-01	6.47E-01	9.30E+02	-0.91	0.36312	
cultivar33Y76:Senrad	-1.16E-01	7.37E-01	9.46E+02	-0.157	0.87528	
cultivar34R67:Senrad	-7.81E-01	6.54E-01	8.84E+02	-1.195	0.23245	
cultivarDKC62-97:Senrad	-6.27E-01	6.23E-01	8.35E+02	-1.007	0.31438	
cultivarDKC63-42:Senrad	-1.20E+00	6.29E-01	8.51E+02	-1.908	0.05667	.
cultivarDKC63-84:Senrad	-1.32E-01	6.30E-01	9.26E+02	-0.209	0.83439	
cultivarDKC64-69:Senrad	-1.37E-01	6.49E-01	8.39E+02	-0.211	0.83317	
cultivarP1151HR:Senrad	-2.45E-01	6.62E-01	9.09E+02	-0.37	0.71139	
cultivarP1173HR:Senrad	-5.93E-01	6.14E-01	8.73E+02	-0.965	0.33479	
cultivarP1395XR:Senrad	-1.13E+00	6.69E-01	9.07E+02	-1.693	0.09075	.
cultivarP1498HR:Senrad	-6.14E-01	6.16E-01	8.50E+02	-0.996	0.31938	
cultivarP1508HR:Senrad	5.61E-02	7.51E-01	1.20E+03	0.075	0.94048	
cultivarP1625HR:Senrad	-4.32E-01	6.02E-01	8.12E+02	-0.718	0.47304	
cultivarP1745HR:Senrad	-1.71E+00	7.76E-01	1.08E+03	-2.2	0.02799	*
cultivarP2088HR:Senrad	-4.88E-01	6.97E-01	1.04E+03	-0.701	0.4837	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

BIBLIOGRAPHY

AEO. “Annual Energy Outlook 2014: Early Release Overview.” *US Energy Information Administration*. February,24 (2014): 1–13.

Aguilera, Eduardo et al. “Managing soil carbon for climate change mitigation and adaptation in Mediterranean cropping systems: A meta-analysis.” *Agriculture, Ecosystems and Environment* 168 (2013) : 25-36.

Andrade, F.H., S.a. Uhart, and a. Cirilo. “Temperature Affects Radiation Use Efficiency in Maize.” *Field Crops Research* 32.1-2 (1993): 17–25.

Asseng, S. “Uncertainty in simulating wheat yields under climate change.” *Nature Climate Change* 3.9 (2013) : 627-632.

Bassu, Simona et al. “How do various maize crop models vary in their responses to climate change factors?” *Global Change Biology* 20.7 (2014) : 2301-2320.

Bates D, Maechler M, Bolker B and Walker S. _lme4: “Linear mixed-effects models using Eigen and S4_.” *R package version 1.1-7* (2014). URL: http://CRAN.R-project.org/package=lme4>

Butler, Ethan E., and Peter Huybers. “Adaptation of US Maize to Temperature Variations.” *Nature Climate Change* 3.1 (2013): 68–72.

Cantarero, M. G., a. G. Cirilo, and F. H. Andrade. “Night Temperature at Silking Affects Kernel Set in Maize.” *Crop Science* 39.3 (1999): 703–710.

Challinor, J. et al. “A Meta-Analysis of Crop Yield under Climate Change and Adaptation.” *NaturreClimate Change* 27.March (2014): 1–5.

Chang, Jen-Hu. “Corn Yield in Relation to Photoperiod, Night Temperature, and Solar Radiation.” *Agricultural Meteorology* 24 (1981): 253–262.

Chung, Uran et al. “Modeling the Effect of a Heat Wave on Maize Production in the USA and Its Implications on Food Security in the Developing World.” *Weather and Climate Extremes* 5-6 (2014): 67–77.

Cicchino, M. et al. “Heat Stress in Field-Grown Maize: Response of Physiological Determinants of Grain Yield.” *Crop Science* 50.4 (2010): 1438–1448.

Cicchino, M., J. I. Rattalino Edreira, and M. E. Otegui. “Heat Stress during Late Vegetative Growth of Maize: Effects on Phenology and Assessment of Optimum Temperature.” *Crop Science* 50.4 (2010): 1432–1436.

Coop, L. B. U. S. degree-day mapping calculator. Version 4.0. *Oregon State University Integrated Plant Protection Center Web Site Publication* E.10-04-1 (2010). URL: http://uspest.org/cgi-bin/usmapmaker.pl

Crafts-Brandner, Steven J, and Michael E Salvucci. "Sensitivity of Photosynthesis in a C4 Plant, Maize, to Heat Stress." *Plant physiology* 129.4 (2002): 1773–1780.

Duncan, W. G., and J. D. Hesketh. "Net Photosynthetic Rates, Relative Leaf Growth Rates, and Leaf Numbers of 22 Races of Maize Grown at Eight Temperatures." *Crop Science* 8.6 (1968): 670.

Duvick, Donald N. "The Contribution of Breeding to Yield Advances in Maize (Zea Mays L.)." *Advances in Agronomy* 86 (2005): 83–145.

Econometric Models of Crop Yield with Implications for Climate Change." *American Journal of Agricultural Economics* 95.2 (2013): 236–243.

FAOSTAT. Rome, Italy: FAO, (2012). Internet resource.

Finger, Robert, Werner Hediger, and Stéphanie Schmid. "Irrigation as Adaptation Strategy to Climate Change-a Biophysical and Economic Appraisal for Swiss Maize Production." *Climatic Change* 105.3-4 (2011): 509–528.

Fovell, Robert G., and Mei-Ying C. Fovell. "Climate zones of the conterminous United States defined using cluster analysis." *Journal of Climate* 6.11 (1993): 2103-2135.

Gbegbelegbe, Sika et al. "Quantifying the Impact of Weather Extremes on Global Food Security: A Spatial Bio-Economic Approach." *Weather and Climate Extremes* 4 (2014): 96–108.

Gholipoor, M. et al. "Maize Hybrid Variability for Transpiration Decrease with Progressive Soil Drying." J*ournal of Agronomy and Crop Science* 199.1 (2013): 23–29.

Gifford, Roger M. "Plant respiration in productivity models: conceptualisation, representation and issues for global terrestrial carbon-cycle research." *Functional Plant Biology* 30.2 (2003): 171-186.

Gustafson, David I. et al. "Climate Adaptation Imperatives: Untapped Global Maize Yield Opportunities." *International Journal of Agricultural Sustainability* 0.0 (2014): 1–16.

Hatfield, J., and G. Takle. "Chapter 6 Agriculture." *Climate Change Impacts in the United States: The Third National Climate Assessment* (2014): 150–174.

Hawkins, Ed, and Rowan Sutton. "The potential to narrow uncertainty in regional climate predictions." *Bulletin of the American Meteorological Society* 90.8 (2009) : 1095-1107.

Hawkins, et al. "Increasing Influence of Heat Stress on French Maize Yields from the 1960s to the 2030s." *Global Change Biology* 19.3 (2013): 937–947.

Jackson, Ray D. "Canopy temperature and crop water stress." *Advances in irrigation* 1 (1982): 43-85.

Kotak, Sachin et al. "Complexity of the Heat Stress Response in Plants." *Current Opinion in Plant Biology* 10.3 (2007): 310–316.

Lenth, Russel V. lsmeans: Least-Squares Means. R package version 2.11 (2014).. http://CRAN.R-project.org/package=lsmeans

Li, Xiang et al. “The Impact of Climate Change on Maize Yields in the United States and China.” *Agricultural Systems* 104.4 (2011): 348–353.

Liu, Zhijuan et al. “Negative Effects of Climate Warming on Maize Yield Are Reversed by the Changing of Sowing Date and Cultivar Selection in Northeast China.” *Global Change Biology* 19.11 (2013): 3481–3492.

Lobell, David B, Wolfram Schlenker, and Justin Costa-Roberts. “Climate Trends and Global Crop Production since 1980.” *Science (New York, N.Y.)* 333.6042 (2011): 616–620.

Lobell, David B., and Gregory P. Asner. "Climate and management contributions to recent trends in US agricultural yields." *Science* 299.5609 (2003): 1032-1032.

Lobell, David B., Graeme L. Hammer, et al. “The Critical Role of Extreme Heat for Maize Production in the United States.” *Nature Climate Change* 3.5 (2013): 497–501.

Lobell, David B., Marianne Bänziger, et al. “Nonlinear Heat Effects on African Maize as Evidenced by Historical Yield Trials.” *Nature Climate Change* 1.1 (2011): 42–45.

McCune, Bruce, James B. Grace, and Dean L. Urban. *Analysis of ecological communities*. Vol. 28. Gleneden Beach, Oregon: MjM software design, 2002.

Mendelsohn, Robert, and Ariel Dinar. “Climate Change, Agriculture, and Developing Countries: Does Adaptation Matter?” *The World Bank Research Observer* 14.2 (1999) : 277-293.

Msangi, Siwa, and Rosegrant, Mark W. “Feeding the Future’s Changing Diets: Implications for Agriculture Markets, Nutrition, and Policy.” *Leveraging Agriculture for ImprovingV Nutrition and Health.* February (2011): 0–4.

Monteith, J. L. "Evaporation and surface temperature." *Quarterly Journal of the Royal Meteorological Society* 107.451 (1981): 1-27.

National Agricultural Statistical Service (NASS). “US irrigated and rainfed maize yield, harvested area and production 2004–2008.” *NASS Marketing and Information Services Office, Washington D.C* 2010. <http://http://www.nass.usda.gov/>

Ortiz-Bobea, Ariel. “The Critical Role of Soil Moisture on U.S. Corn Yields and Its Implications for Climate Change.” *Forthcoming* (2015): 1–58.

Otegui, M. E., and R. Bonhomme. “Grain yield components in maize I. Ear growth and kernel set.” *Field Crops Research* 56.3 (1998) : 257-264.

Refsgaard, J. C. et al. “A framework for testing the ability of models to project climate change and its impacts.” *Climatic Change* 122.1-2 (2014) : 271-282.

Rivington, Mike, and Jawoo Koo. “Report on the Meta- Analysis of Crop Modelling for Climate

Change and Food Security Survey." CCAFS, 2011.

Roberts, Michael J., Wolfram Schlenker, and Jonathan Eyer. "Agronomic Weather Measures in Econometric Models of Crop Yield with Implications for Climate Change." *American Journal of Agricultural Economics* 95.2 (2013): 236–243.

Rosegrant, Mark W et al. "Agriculture and Food Security under Global Change : Prospects for 2025 / 2050." (2009) : 0-81.

Russell, W. A. "Genetic improvement of maize yields." *Advances in Agronmy* 46 (1991): 245-298.

Schlenker, Wolfram, and David B Lobell. "Robust negative impacts of climate change on African agriculture." *Environmental Research Letters* (2010) : 014010.

Schlenker, Wolfram, Michael J. Roberts, and David B. Lobell. "US Maize Adaptability." *Nature Climate Change* 3.8 (2013): 690–691.

Seneviratne, Sonia I., et al. "Changes in climate extremes and their impacts on the natural physical environment." *Managing the risks of extreme events and disasters to advance climate change adaptation* (2012): 109-230.

Shaw, Stephen B., Dhaval Mehta, and Susan J. Riha. "Using Simple Data Experiments to Explore the Influence of Non-Temperature Controls on Maize Yields in the Mid-West and Great Plains." *Climatic Change* (2014): 1–9.

Sinsawat, Veerana et al. "Effect of Heat Stress on the Photosynthetic Apparatus in Maize (Zea Mays L.) Grown at Control or High Temperature." *Environmental and Experimental Botany* 52.2 (2004): 123–129.

Smith, Stephen et al. "Maize." *Yield Gains in Major U.S. Field Crops* 50063 (2014): 125–172.

Snyder, R., and W. Pruitt. "Estimating reference evapotranspiration with hourly data." *Chapter VII* 1 (1985).

Stephen W. Raudenbush, and Anthony S. Bryk. *Hierarchical linear models: Applications and data analysis methods*. Vol. 1. Sage, 2002.

Sung, Dong Yul et al. "Acquired Tolerance to Temperature Extremes." *Trends in Plant Science* 8.4 (2003): 179–187.

Suyker, Andrew E., et al. "Gross primary production and ecosystem respiration of irrigated maize and irrigated soybean during a growing season." *Agricultural and Forest Meteorology* 131.3 (2005): 180-190.

Tao, Fulu, and Zhao Zhang. "Adaptation of Maize Production to Climate Change in North China Plain: Quantify the Relative Contributions of Adaptation Options." *European Journal of Agronomy* 33.2 (2010): 103–116.

Tokatlidis, I. S., and S. D. Koutroubas. "A Review of Maize Hybrids' Dependence on High Plant

Populations and Its Implications for Crop Yield Stability." *Field Crops Research* 88.2-3 (2004): 103–114.

Tollenaar, M., and E. Lee. "Yield Potential, Yield Stability and Stress Tolerance in Maize." *Field Crops Research* 75.2-3 (2002): 161–169.

United Nations / Department of Economic and Social Affairs. "World Population Prospects : The 2008 Revision." *Population Newsletter* 87 (2009): 1–20.

Urban, Daniel et al. "Projected Temperature Changes Indicate Significant Increase in Interannual Variability of U.S. Maize Yields: A Letter." *Climatic Change* 112.2 (2012): 525–533.

Urban, Daniel W, Justin Sheffield, and David B Lobell. "The Impacts of Future Climate and Carbon Dioxide Changes on the Average and Variability of US Maize Yields under Two Emission Scenarios." *Environmental Research Letters* 10.4 (2015): 45.

Wickham, H. "ggplot2: elegant graphics for data analysis." Springer New York (2009).

Winstanley, D, and S. Changnon. "Long-Term Variations in Seasonal, Weather Conditions Important to Water Resources in Illinois." *Journal of the American Water Resources Association* 35.6 (1999): 1421–1427.

Zuur, Alain, et al. *Mixed effects models and extensions in ecology with R*. Springer Science & Business Media, 2009.